NTIRE 2017 Challenge on Single Image Super-Resolution: Methods and Results

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Abstract

This paper reviews the first challenge on single image super-resolution (restoration of rich details in an low resolution image) with focus on proposed solutions and results. A new DIVerse 2K resolution image dataset (DIV2K) was employed. The challenge had 6 competitions divided into 2 tracks with 3 magnification factors each. Track 1 employed the standard bicubic downscaling setup, while Track 2 had unknown downscaling operators (blur kernel and decimation) but learnable through low and high res train images. Each competition had ~ 100 *registered participants and 20 teams competed in the final testing phase. They gauge the state-of-the-art in single image super-resolution.*

1. Introduction

Example-based single image super-resolution (SR) aims at the restoration of rich details (high frequencies) in an image based on a set of prior examples with low resolution (LR) and corresponding high resolution (HR) images. The loss in image content can be due causes such as quantization error, limitations of the sensor from the capturing camera, the presence of blur or other degrading operators and the use of downscaling operators to reduce the image resolution for storage purposes. SR is ill-posed, since for each LR image the space of corresponding HR images can be very large.

In recent years a significant amount of literature focused on example-based single image super-resolution research. The performance of the top methods continuously improved [41, 33, 17, 18] showing that the field reaches maturity. Yet, the field lacks standardized benchmarks to allow for an assessment that is based on identical image datasets and criteria. Recently, most single image SR publications use the 91 train images of Yang *et al*. [41], the three test image sets (Set5 [3], Set14 [42], B100 [22, 33]) brought together by Timofte *et al*. [32, 33] and a bicubic downscaling (imresize from Matlab) to simulate the HR to LR transformation. This standard setup allowed for substantial improvement, but has significant shortcomings: (1) small train set: only 91 small size images with jpeg artifacts (some works [17, 18] already adopted BSD [22] and ImageNet [26] for extra train images); (2) small test sets and image sizes (often below 500×500 pixels); (3) bicubic downscaling is a oversimplification of the real conditions.

The NTIRE 2017 challenge is a step forward in benchmarking example-based single image super-resolution. It uses 1000 DIVerse 2K resolution images (DIV2K) dataset and two types of degradations: the standard bicubic and the unknown downscaling operators *aka* downscaling operators known only through train data of LR and corresponding HR

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Appendix A contains the authors' teams and affiliations.
NTIRE webpage: `http://www.vision.ee.ethz.ch/ntire17/`

images. The DIV2K dataset is introduced in [1] along with a study of the challenge results in relation with the prior art. In the next we describe the challenge, present and discuss the results and describe the methods.

2. NTIRE 2017 Challenge

The objectives of the NTIRE 2017 challenge on example-based single-image super-resolution are: (i) to gauge and push the state-of-the-art in SR; (ii) to compare different solutions; (iii) to promote a novel large dataset (DIV2K); and (iv) more challenging SR settings.

2.1. DIV2K Dataset

Complementary with the small sized and low resolution SR datasets commonly used, a novel dataset is promoted, namely DIV2K dataset [1]. It consists from 1000 DIVerse 2K resolution RGB images. 800 are for training, 100 for validation and 100 for testing purposes. The images are of high quality both aesthetically and in the terms of small amounts of noise and other corruptions (like blur and color shifts). All images were manually collected and have 2K pixels on at least one of the axes (vertical or horizontal). DIV2K covers a large diversity of contents, from people, handmade objects and environments (cities), to flora and fauna, natural sceneries, including underwater.

2.2. Tracks and competitions

Track 1: Bicubic downscaling ('classic') facilitates the easy deployment of recent proposed methods for the task of example-based single-image super-resolution. It assumes that the degradation operators are the same as commonly used in the recent SR literature. Each LR image is obtained from the HR DIV2K image by using Matlab function 'imresize' with default settings (bicubic interpolation) and the downscaling factors: 2, 3, and 4.

Track 2: Unknown downscaling goes on step ahead and considers that at runtime we know the LR image and a set of (training) pairs of LR and corresponding HR images. No Gaussian or other types of noise is added to the images, only blur and decimation. No other information is provided about the degrading operators producing the downscaling images. Each ground truth HR RGB image from DIV2K is downscaled (by factor 2, 3, and 4) to corresponding LR images and used either for training, validation, or testing of the methods.

Competitions For each track there is a competition per each downscaling factor (2, 3, and 4). CodaLab platform was used for all 6 competitions of NTIRE 2017 challenge. To access the data and submit their HR image results to the CodaLab evaluation server each participant had to register.

https://competitions.codalab.org

Challenge phases *(1) Development (training) phase:* the participants got both LR and HR train images and the LR images of the DIV2K dataset; *(2) Validation phase:* the participants had the opportunity to test their solutions on the LR validation images and to receive immediate feedback by uploading their results to the server. A validation leaderboard is available; *(3) Final evaluation (test) phase:* the participants got the LR test images and had to submit both their super-resolved image and a description of their methods before the challenge deadline. One week later the final results were made available to the participants.

Evaluation protocol The Peak Signal-to-Noise Ratio (PSNR) measured in deciBels (dB) and the Structural Similarity index (SSIM) [35] computed between an image result and the ground truth are the quantitative measures. The higher the score is the better the restoration fidelity to the ground truth image. A rim of $6+s$ image pixels, where s is the magnification factor, are ignored in the evaluation.

3. Challenge Results

From 100 registered participants on average per each competition, 20 teams entered in the final phase and submitted results, codes/executables, and factsheets. Table 1 reports the final scoring results of the challenge and Table 2 shows the runtimes and the major details for each entry. Section 4 describes briefly the methods for each team while in the Appendix A are the team members and affiliations.

Architectures and main ideas All the proposed methods, excepting WSDSR, use the end-to-end deep learning and employ the GPU(s) for both training and testing. The very deep super-resolution net (VDSR) using VGG-16 CNN architecture [17] and the deep residual nets (ResNet) architecture [13, 18] are the basis for most of the proposed methods. Lab402 and iPAL prefer to work in the wavelet domain for both efficiency and robustness. They convert the RGB images and then use a deep ResNet to process the wavelet data. iPAL is the fastest GPU method (0.1s per image), however it ranks 12 on average in Track 1, while Lab402 goes deeper with the nets and a winner of the challenge, ranks 3rd overall. For design efficiency and for speeding up the training some solutions (such as VICLab,HIT-ULSee,UIUC-IFP,nicheng) employ the sub-pixel layer [28], other remove the batch normalization layers (SNU_CVLab), stack nets (HelloSR,GTY,Resonance), jointly train subnets ('I hate mosaic'), firstly deblur then upscale the image (DL-61-86), jointly deblur (using multi-scales) and upscale (SR2017) or treats SR as a motion prediction (SDQ_SR). WSDSR is a self-similarity approach based on BM3D and Wiener filter. WSDSR does not use train data only the LR image. However, it is the slowest method (more than 0.5h per image on CPU) on Track 1.

Restoration fidelity SNU_CVLab, HelloSR and Lab402 are the best scoring teams and ***the winners of NTIRE 2017***

Team	User	Track 1: bicubic downscaling						Track 2: unknown downscaling					
		$\times 2$		$\times 3$		$\times 4$		$\times 2$		$\times 3$		$\times 4$	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SNU_CVLab [1]	limbee	$34.93_{(1)}$	0.948	$31.13_{(1)}$	0.889	$26.91^{*}_{(14)}$	0.752^{*}	$34.00_{(1)}$	0.934	$30.78_{(1)}$	0.881	$28.77_{(1)}$	0.826
SNU_CVLab [2]	sanghyun	$34.83_{(2)}$	0.947	$31.04_{(2)}$	0.888	$29.04_{(1)}$	0.836	$33.86_{(2)}$	0.932	$30.67_{(2)}$	0.879	$28.62_{(2)}$	0.821
HelloSR	sparkfirer	$34.47_{(4)}$	0.944	$30.77_{(4)}$	0.882	$28.82_{(3)}$	0.830	$33.67_{(3)}$	0.930	$30.51_{(3)}$	0.876	$28.54_{(3)}$	0.819
Lab402	iorism	$34.66_{(3)}$	0.946	$30.83_{(3)}$	0.884	$28.83_{(2)}$	0.830	$32.92_{(7)}$	0.921	$30.31_{(4)}$	0.871	$28.14_{(6)}$	0.807
VICLab	JSChoi	$34.29_{(5)}$	0.943	$30.52_{(5)}$	0.880	$28.55_{(5)}$	0.845						
UIUC-IFP	fyc0624	$34.19_{(6)}$	0.942	$30.44_{(7)}$	0.877	$28.49_{(6)}$	0.821	$28.54_{(14)}$	0.840	$28.11_{(14)}$	0.816	$24.96_{(15)}$	0.717
HIT-ULSee	chenyunjin	$34.07_{(7)}$	0.941	$30.21_{(9)}$	0.871	$28.49_{(6)}$	0.822	$33.40_{(4)}$	0.927	$30.21_{(6)}$	0.871	$28.30_{(4)}$	0.812
I hate mosaic	tzm1003306213	$34.05_{(8)}$	0.940	$30.47_{(6)}$	0.878	$28.59_{(4)}$	0.824						
nicheng	nicheng									$30.24_{(5)}$	0.871	$28.26_{(5)}$	0.811
GTY	giangbui	$34.03_{(9)}$	0.941	$30.24_{(8)}$	0.874	$28.34_{(7)}$	0.817	$33.32_{(5)}$	0.926	$30.14_{(7)}$	0.869	$27.33_{(8)}$	0.785
DL-61-86	rosinwang							$33.10_{(6)}$	0.922	$30.05_{(8)}$	0.863	$28.07_{(7)}$	0.800
faceall_Xlabs	xjc_faceall	$33.73_{(10)}$	0.937	$30.07_{(10)}$	0.869	$27.99_{(10)}$	0.805	$24.98_{(15)}$	0.707	$29.87_{(9)}$	0.862	$26.84_{(10)}$	0.762
SR2017	xiangyu_xu	$33.54_{(11)}$	0.934	$29.89_{(12)}$	0.865	$28.07_{(8)}$	0.809	$29.92_{(12)}$	0.871	$28.84_{(11)}$	0.836	$26.05_{(11)}$	0.754
SDQ_SR	XibinSong	$33.49_{(12)}$	0.936					$32.35_{(8)}$	0.912				
HCILab	phunghx	$33.47_{(13)}$	0.934	$29.92_{(11)}$	0.866	$28.03_{(9)}$	0.807	$31.13_{(9)}$	0.896	$29.26_{(10)}$	0.849	$25.96_{(12)}$	0.749
iPAL	antonGo	$33.42_{(14)}$	0.932	$29.89_{(12)}$	0.865	$27.99_{(10)}$	0.806						
WSDSR	cristovao.a.cruz	$33.19_{(15)}$	0.933	$29.74_{(13)}$	0.864	$27.92_{(11)}$	0.805						
Resonance	arnavkj95							$30.21_{(10)}$	0.889	$28.43_{(13)}$	0.840	$24.79_{(16)}$	0.724
zrfanzy	zrfan	$31.87_{(17)}$	0.927	$28.80_{(15)}$	0.858	$27.67_{(12)}$	0.800	$21.94_{(16)}$	0.618	$18.03_{(15)}$	0.490	$26.95_{(9)}$	0.773
assafsho	assafsho	$30.39_{(18)}$	0.894	$27.23_{(16)}$	0.806	$25.74_{(15)}$	0.742						
UESTC-kb545	naiven											$25.08_{(14)}$	0.714
spectrum	spectrum							$28.76_{(13)}$	0.854				
bicubic interp.	*baseline*	31.01	0.900	28.22	0.822	26.65	0.761	25.08	0.713	25.81	0.736	21.84	0.583

Table 1. NTIRE 2017 Challenge results and final rankings on DIV2K test data. (*) the checked SNU_CVLab[1] model achieved 29.09dB PSNR and 0.837 SSIM.

Team	Track 1: bicubic downscaling			Track 2: unknown downscaling			Platform	CPU (at runtime)	GPU (at runtime)	Architecture (at runtime)	Ensemble / Fusion (at runtime)
	$\times 2$	$\times 3$	$\times 4$	$\times 2$	$\times 3$	$\times 4$					
SNU_CVLab [1]	67.240	28.720	20.050	8.778	4.717	2.602	Torch (Lua)		GTX TITAN X	36 ResBlocks	Track1: flip/rotation ($\times 8$), Track2: 2 models
SNU_CVLab [2]	14.070	7.340	5.240	4.600	2.310	1.760	Torch (Lua)		GTX TITAN X	80 ResBlocks	Track1: flip/rotation ($\times 8$), Track2: 2 models
HelloSR	27.630	27.970	18.470	11.540	19.260	15.360	Torch (Lua)		GTX TITAN X	stacked ResNets	Track1: flip/rotation ($\times 4$), Track2: 2/3 models
Lab402	4.080	5.120	5.220	4.120	1.880	1.120	Matconvnet+Matlab		GTX 1080ti	wavelet+41 conv. layers	none
VICLab	0.539	0.272	0.186				Matconvnet		TITAN X Pascal	22 layers	none
UIUC-IFP	1.683	1.497	1.520	1.694	1.474	1.523	TensorFlow+Python		$8\times$GPUs	6+4 ResBlocks	flip/rotation ($\times 8$)
HIT-ULSee	0.370	0.160	0.100	0.370	0.160	0.100	Matlab		Titan X Pascal	20 (sub-pixel) layers	none
I hate mosaic	10.980	8.510	8.150				TensorFlow+Python		Titan X Maxwell	Joint ResNets	rotation ($\times 4$)
nicheng					0.241	0.175	Torch (Lua)		Titan X Pascal	modified SRResNet	none
GTY	4.400	4.230	4.320	4.370	4.390	4.210	Theano (Lasagne)		Titan X	stacked 4 modified VDSRs	none
DL-61-86				2.220	3.650	1.160	Torch7 + Matlab		Geforce GTX 1080	blind deconv+SRResNet	none
faceall_Xlabs	0.050	0.050	0.050	0.050	0.050	0.050	PyTorch / Matlab caffe		GTX-1080	20/9 layers ResNet	none
SR2017	2.480	2.480	2.540	2.500	2.470	2.470	Matlab + caffe		GTX1080	multi-scale VDSR	none
SDQ_SR	3.100			10.080			Matlab		Titan X?	motion prediction+VDSR	none
HCILab	0.852	0.851	0.858	0.897	0.867	0.856	caffe+cudnn		Titan X	VDSR-based	none
iPAL	0.092	0.091	0.093				TensorFlow+Python		Titan X	wavelet+10 layers CNN	none
WSDSR	1678.000	2578.000	2361.000				Matlab+mex	✓		iter. back proj+modif.BM3D	none
Resonance				6.730	3.830	7.020	Theano (Keras)		Titan X?	2 nets, Inception ResBlocks	none
zrfanzy	16.150	13.440	11.640	11.370	12.790	13.560	TensorFlow+Python		Titan X?	modified SRResNet	none
assafsho	33.010	23.920	19.850								
UESTC-kb545						11.390	TensorFlow		GTX 1080	2-way RefineNet / ResNet	none
spectrum				40.000							
bicubic interp.	0.029	0.014	0.009	0.029	0.014	0.009	Matlab	✓		imresize function	none

Table 2. Reported runtimes per image on DIV2K test data and details from the factsheets.

challenge. SNU_CVLab with single-scale nets achieves 34.93dB for Track 1 & $\times 2$ and 34.00dB for Track 2 & $\times 2$, almost +4dB and +9dB, respectively, better than the bicubic interpolation baseline results. SNU_CVLab achieves the best results for all the 6 competitions. If in PSNR terms the differences are significant, in SSIM terms the best entries in each competition are very close (SSIM varies from 0.948 (1st result) to 0.940 (8th result) for Track1& $\times 2$) and show the limitation of the SSIM.

Runtime / efficiency In Figs. 1& 2 we plot runtime per image vs. achieved PSNR performance for two competitions. HIT-ULSee solution is ***the most efficient***, it gives the best trade-off between runtime and quality of the results. It runs in 0.1s for $\times 4$, on Titan X Pascal GPU while being only 0.5dB below the best reported result of SNU_CVLab which is much slower: 20s on (Track1, $\times 4$) and 2.6s on (Track 2, $\times 4$).

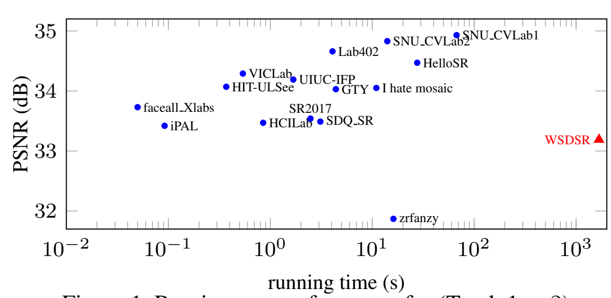


Figure 1. Runtime vs. performance for (Track 1, $\times 2$).

Ensembles and fusion Only SNU_CVLab, HelloSR, UIUC-IFP, and 'I hate mosaic' used ensembles of methods/results to boost their performance. The common approach is the enhanced prediction or multi-view processing [34, 36] which assumes flips and rotations (in 90° steps) of the input LR image to obtain 4 or 8 HR results that are

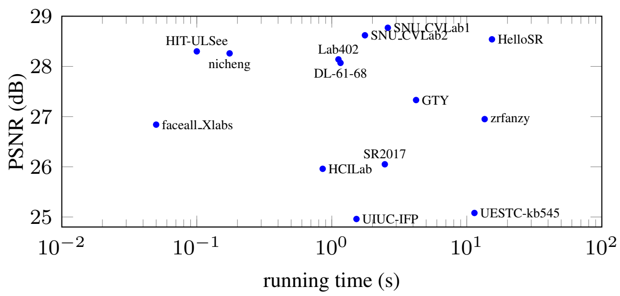


Figure 2. Runtime vs. performance for (Track 2, ×4).

aligned back through the inverse transformation and averaged to get the final result. On Track 2 this approach can not be applied as the degradation operators (blur kernel) are variant with the rotation or flip. Therefore, only the first teams deployed 2 or 3 models per each competition and averaged their results. SNU_CVLab used different losses to train their ensemble models.

Train data DIV2K dataset [1] has 800 train images and all the competitors found the amount of data sufficient for training their model, especially after data augmentation (by operations such as flipping, rotation, scaling [34]). For Track 2 SNU_CVLab first learned the HR to LR mapping to then generate more train data by applying the mapping on extra images collected from Flickr.

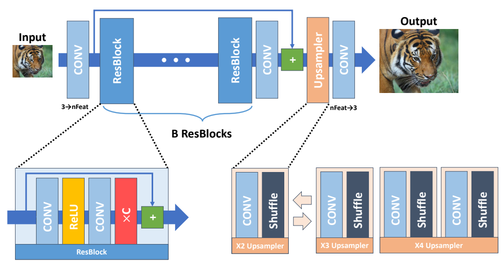
Conclusions By analyzing the challenge methods and their results we can draw several conclusions. **(i)** The proposed solutions have a degree of novelty and go beyond the published state-of-the-art methods. **(ii)** The top solutions are consistent for all 6 competitions, showing that they generalize well for both bicubic and unknown downscaling with different magnification factors (2,3, and 4) given that sufficient train data is provided. **(iii)** As expected, the unknown downscaling track is more challenging than the bicubic one and this is reflected by the relatively lower PSNR (up to 1dB for the winners) of the results. **(iv)** SSIM is unable to capture the differences between the SR solutions. Other (perceptual) measures are more relevant (see the studies in [1, 40]). **(v)** The community would benefit from a more realistic setup including complex combinations of degradation factors (blur, decimation, noise) in a uniform and/or non-uniform manner.

4. Challenge Methods and Teams

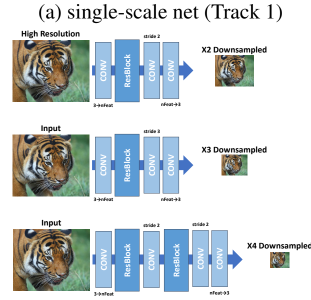
4.1. SNU_CVLab team

SNU_CVLab delves into SRResNet architecture [18, 13] and better optimizes it with several modifications [20]. First, removes unnecessary modules and produces a simpler model architecture. For each NTIRE 2017 challenge track, a model is trained that super resolves given images with the corresponding scale. Second, SNU_CVLab further reduces model complexity by constructing a new multi-task model in a single structure. A model is build that can super resolves an image in multiple scales simultaneously.

SNU_CVLab solution 1: single-scale nets



(a) single-scale net (Track 1)

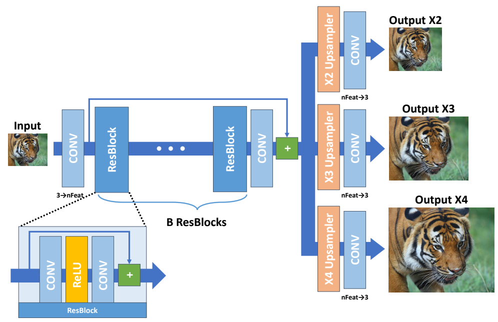


(b) downsamplers (Track 2)

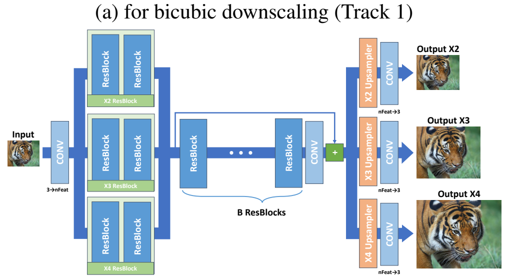
Figure 3. SNU_CVLab team: single-scale architectures, solution 1

A new building block is constructed by removing batch normalization layers [16] from the residual blocks (ResBlock) in [13]. Contrary to high-level vision tasks, removing batch normalization layers is sometimes beneficial in terms of PSNR. Also, a residual scaling layer (constant multiplication) is added after the second convolutional layer of the block. Empirically is found that setting this constant C = 0.1 stabilizes the learning procedure, especially when the number of feature maps is large. The model as an end-to-end CNN with 36 such modified residual blocks (ResBlocks) (see Fig. 3). Each block is composed of 3×3 convolutional layers with 256 feature maps. A single-scale model is trained for each challenge track and only the upsampling modules differ for each scale factor. At training time, the input patch size is set to 48×48 and the mini-batch size to 16. The model is trained with l_1 loss using an ADAM optimizer with learning rate 1×10^4. The learning rate is halved after every 2×10^5 iterations. For the Track 1, the $\times 3$ and $\times 4$ models are trained starting from the pretrained model for $\times 2$ while the upsampling modules are randomly initialized. The train DIV2K train data is augmented with vertical/horizontal flips and 90° rotations. At runtime, vertical/horizontal flips and 90° rotations are used to generate 8 images that are processed and then the results averaged as in [34, 36]. For the Track 2 first the downsampling operators are learned using the nets from Fig. 3(b). The nets are used to augment the train data (by rotations and flip) and also to generate new train data from the newly crawled Flickr2K dataset with 2650 HR images from flickr.com. 2

additional ResBlocks are used for each scale in Track 2. Supplementary, two models were trained and their results averaged at runtime: one using l_1-norm loss and another with $loss = \|SR - HR\|_1 + \|\nabla SR - \nabla HR\|_1$.



(a) for bicubic downscaling (Track 1)



(b) for unknown downscaling (Track 2)

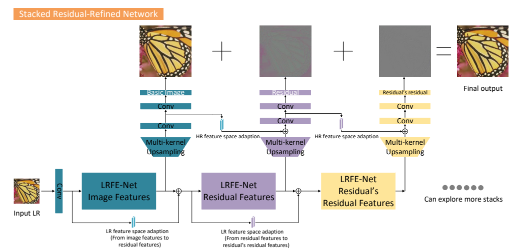
Figure 4. SNU_CVLab team: multi-scale architectures, solution 2

SNU_CVLab solution 2: multi-scale nets

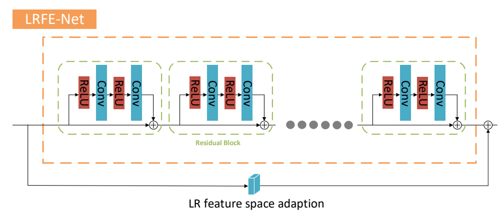
SNU_CVLab makes their model compact by estimating HR images at multiple scales simultaneously. In contrast to the single-scale model, the multi-scale model includes multiple upsampling modules at the end as shown in Fig. 4. Thus, the multi-scale model can estimate $\times 2$, $\times 3$, $\times 4$ HR image while keeping the increase in number of parameters small. At training time, a SR scale among 2, 3 and 4 is chosen at random for each minibatch. For upsampling modules, only parameters for the selected scale is updated. 80 ResBlocks with 64 feature maps and three upsampling modules are used to build the multi-scale model. As the number of feature maps is not large, a residual scaling layer was not used. For training, the input patch size is set to 64×64. For Track 1, the same train and test procedures are followed as for the single-scale solution, only this time with a multi-scale compact model. For Track 2, as in the single-scale case, the train data is augmented and extra data is used (Flickr2K) and also ensembles of two models are used.

4.2. HelloSR team

HelloSR proposes a novel stacked residual-refined network design (see Fig. 5) inspired by the effectiveness of learning high-frequency residuals for SR [41, 32, 5, 17]. The model consists of three stacks marked in blue, purple and yellow, resp. Each stack consists of a LR feature extraction module (LRFE-Net), a multi-kernel upsampling module (Fig. 6), and a reconstruction module from HR features. The blue stack recovers the basic SR image, the purple one recovers the residual of an image, while the yellow one recovers the residuals residual of an image. Therefore, the model performs SR operation in a coarse-to-fine manner. The LR and HR feature space adaptations serve as the bridges. More stacks can be consecutively placed together. For the challenge only up to three levels were explored.



(a) Stacked Residual-Refined Network

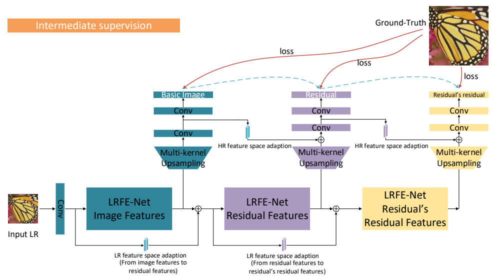


(b) LR Feature Extraction network

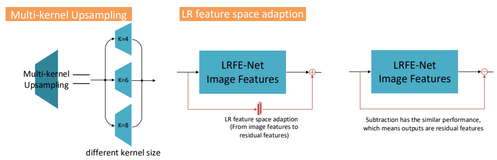
Figure 5. HelloSR team: proposed architectures.

Intermediate supervision to each of the stacks as in [24], shown in Fig. 6(a), helps the training convergence of each stack. At the end, the intermediate supervision is removed and an end-to-end optimization is applied with the final loss. The adaptation of the features from a stack to another, called here **features space adaptation**, is done by 1×1 convolutional layers. In LRFE skip connections are used as well. To ease the training of the network and improve its power, **preserving the negative information** is important [19] as well as the pre-activations and the skip connections [14]. In LRFE-Net the residual blocks adopt pre-activation strategy and LeakyReLU (with parameters 0.2) is used instead of ReLU in the HR feature part. In the LR feature part, negative information can be preserved by residual blocks. The upsampling operation is performed by the deconvolutional layers [10, 15] and a multi-kernel upsampling is used (see Fig. 6(b)).

The same network structure is used for training models for each competition, only the specification of the multi-kernel upsampling layers changes. All the models work on RGB [9] and are trained from scratch on DIV2K train data. The train DIV2K images are cropped to small sub-images (480×480) and further 32×32 randomly cropped patches are used from the sub-images. The loss is the Charbonnier function. For Track 1, at test, the back projection and rotations with $90°$ to generate 4 images and averaged results as output [34] are used, while for track 2 are used ensembles of 2 (for $\times 2$) and 3 models (for $\times 3$ and $\times 4$).



(a) intermediate supervision



(b) multi kernel upsampling and feature space adaptation

Figure 6. HelloSR team: supervision, upsampling and adaptation.

4.3. Lab402 team

A 41 layers wavelet residual network based on persistent homology analysis of the data manifold in the feature space is proposed by Lab402. The Haar wavelet transform [4] can annihilate the smoothly varying signals while maintaining the image edges, which results in simpler manifolds. A long bypass connection is used to mitigate the gradient vanishing problem. In addition, a sub-pixel shuffling based on [28] and residual learning are used. The basic design and ideas are introduced in detail in [2]. The challenge networks details are summarized in Fig. 7 and Table 3.

Each model is trained on DIV2K train images with a patch size of 20x20, batch size of 64, learning rate of $(0.1, 0.00001)$ in logscale, 0.0001 weight decay, 0.9 momentum and 0.05 gradient clipping, for 150 epochs. It is used the sub-epoch system that repeats forward and back-propagation 512 times by using randomly cropped patches per a single image. Training takes almost 7 days with GTX 1080ti. For bicubic $\times 3$ and $\times 4$, the models are trained with all data from bic. $\times 2$, $\times 3$ and $\times 4$, for data augmentation.

	Bicubic x2 (256ch)	Bicubic x3,x4 (320ch)	Unknown x2,x3,x4(320ch)
Input	WT(BU(LR))		COPY_ch(LR)
Label	Input - WT(HR)		Input - PS(HR)
1st layer	Conv $\rightarrow$ ReLU		
2nd layer	Conv $\rightarrow$ BN $\rightarrow$ ReLU		
LB layer	LB(1)	-	-
1st module	BypassM1→Conv→BN→ReLU→ Conv→BN→ ReLU→Conv →BN→SumF(BypassM1) →ReLU		
Repeat 1st module	$5\times$ ($2 \sim 6$ module)	$11\times$ ($2 \sim 12$ module)	$12\times$($2 \sim 12$ module)
LB & layer catch	$\sum$(LB(1)+'Output of 6th module'→ BN→ ReLU	-	-
LB layer	LB(2)	-	-
Repeat 1st module	$6\times$ ($7 \sim 12$ module)	-	-
LB & layer catch	$\sum$(LB(2)+'Output of 12th module')→ BN→ ReLU	-	-
Last layer	Conv→BN→ReLU→Conv→BN→ReLU→Conv		
Restoration	IWT(Input-Output)		IPS(Input-Output)

* WT: haar Wavelet Transform, BU: Bicubic Upsampling, LR: Low Res image, HR: High Res image, Conv: 3x3 Convolution, BN: Batch Normalization, BypassM: send output to last layer of module, LB: Long Bypass, SumF: Sum of output of previous layer and BypassM output, COPY_ch: Copy input image (scale x scale) times on channel direction, PS: sub-Pixel Shuffling, IPS: Inverse sub-Pixel Shuffling, IWT: Inverse Wavelet Transform

Table 3. Lab402 team: details of the proposed nets.

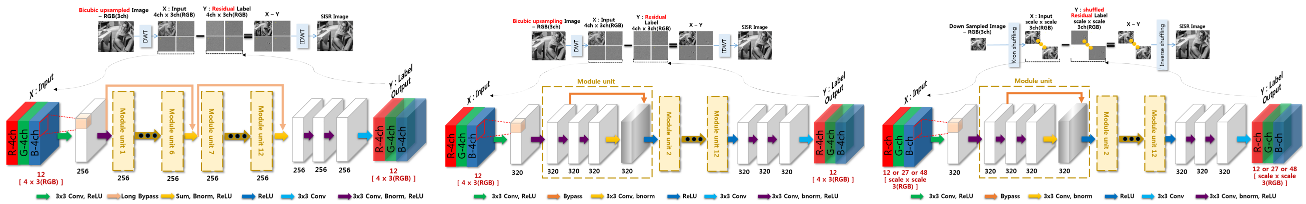
4.4. VICLab team

The proposed solution uses a novel 22-layered deep network architecture with selection units (see Fig. 8 and [6]). The rectified linear unit (ReLU) has been widely used in deep-learning literatures and VICLab found that ReLU can be re-defined as a point-wise multiplication of a linear unit and a switch unit (0 for < 0 and 1 for ≥ 0). In this sense, ReLU does not have control over which element to pass or not, because a derivative of a switch unit is 0 and the error cannot be back-propagated through this unit. By using sigmoid instead of the switch unit, we have come up with a novel nonlinear unit: selection unit, which is a multiplication of a linear unit and a sigmoid. Experiment results show that any network structure with our selection units outperforms conventional network structure with ReLU or sigmoid. Furthermore, the proposed architecture jointly incorporates residual units, residual learning [17], gradient clipping [17] and sub-pixel convolutions [28] for faster learning and higher performance. The size of the output after the final convolution layer is $W \times H \times (s^2 \times 3)$, where $W \times H$ is the size of LR image, and s is a scaling factor. This output is converted to $(W \times s) \times (H \times s) \times 3$-sized RGB HR image.

4.5. UIUC-IFP team The proposed balanced two-stage residual networks (BTSRN) [11] contains LR and HR stages with 6 and 4 residual blocks [13], resp. The two stages are connected by element sum of nearest neighbor up-sampling and de-convolution. Compared with VDSR [17], the proposed approach takes LR image as input and reduces the computational redundancy; compared with ESPCN [28], SRGAN [18] and EnhanceNet [27], the proposed model performs better refinement in the HR space and yields fewer checkerboard artifacts. The proposed residual block (see Fig. 9) achieves the overall best trade-off between the accuracy and the speed among several tried architectures. The model learns the residual between HR images and bicubic up-sampled LR ones. For $\times 4$, the up-sampling module is decomposed into two $\times 2$ up-sampling modules. The models for each track and upscaling factor were trained separately.

4.6. HIT-ULSee team The solution incorporates the sub-pixel layer [28] into a denoising CNN [43] for fast and effective SR (see Fig. 11). The proposed network takes the color LR image as input. A SR network with upscaling factor s uses 128 filters of size $3 \times 3 \times 3$ to generate 128 feature maps in the first convolution layer, while in the last convolution layer, uses $3s^2$ filters of size $3 \times 3 \times 128$. The middle layers use 128 filters of size $3 \times 3 \times 128$. In the final sub-pixel layer, $3s^2$ LR feature maps are merged into the residual with desired size via the sub-pixel layer. Then the bicubically interpolated LR input is added. The depth is set to 20 layers. Zeros are padded before each convolution to ensure that each feature map of the middle layers has the size of the input LR image. A leaky ReLU function $f(x) = max(x, 0.05x)$ is used as activation function. For each competition a separate model was trained.

4.7. 'I hate mosaic' team A two nets architecture solution which uses a parameter shared network and a color prior network (see Fig. 12). Different color channels share the same downscaling operator and part of model parameters



(a) Bicubic ×2 (b) Bicubic ×3, ×4 (320ch) (c) Unknown ×2, ×3, ×4 (320ch)

Figure 7. Lab402 team: the proposed nets for challenge tasks.

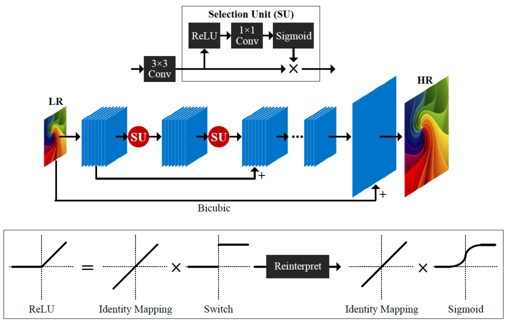


Figure 8. VICLab team: proposed network with selection unit.

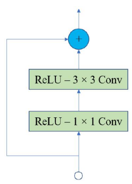


Figure 9. UIUC-IFP team: proposed residual block.

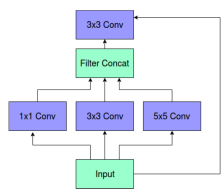


Figure 10. Resonance team: an inception ResNet block.

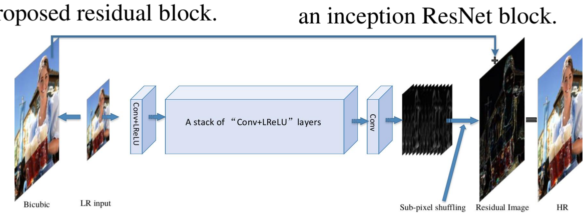
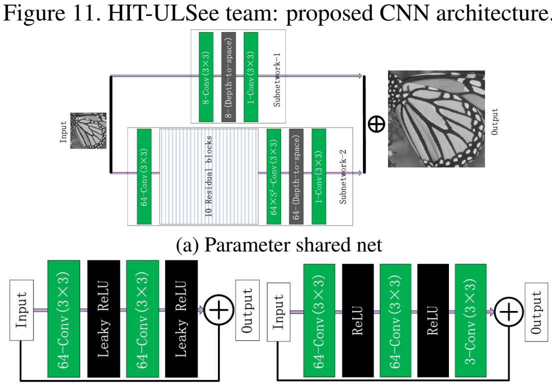


Figure 11. HIT-ULSee team: proposed CNN architecture.



(a) Parameter shared net

(b) ResBlock in parameter shared net (c) ResBlock in color prior net

Figure 12. 'I hate mosaic' team: nets and residual blocks.

to exploit cross channel correlation constraints [23]. Another net is deployed to learn the difference among different color channels and color prior. Upsampling module upscale feature maps from LR to HR via depth-to-space convolution (aka sub-pixel convolution). A shallow and extremely simple sub-network is used to reduce the low-frequent redundancy [31] and to accelerate training. The color prior network has 6 residual blocks. This objective function is robustified (includes a variant of MSE and a differentiable variant of l_1 norm) to deal with the outliers in training.

4.8. nicheng team A SRResNet [18]-based solution with a couple of modifications (see Fig. 13. For ×4, the nearest-neighbour interpolation layer replaces the sub-pixel layer, otherwise the sub-pixel layer would cause the checkerboard pattern of artifacts [25]. Also the input is interpolated and added to the network output as in [17]. ×3 model uses the pixel shift method to up-sample the image.

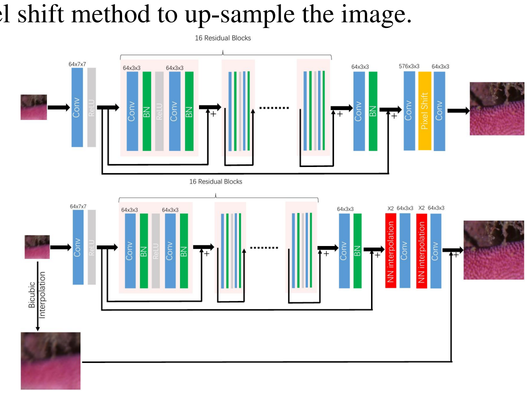


Figure 13. nicheng team: SRResNet modif. models for ×3 & ×4.

4.9. GTY team Four modified VDSR nets [17] (PReLU instead of ReLu, RGB channels instead of one) are stacked and their outputs are linearly combined to obtain the final HR output as shown in Fig. 14.

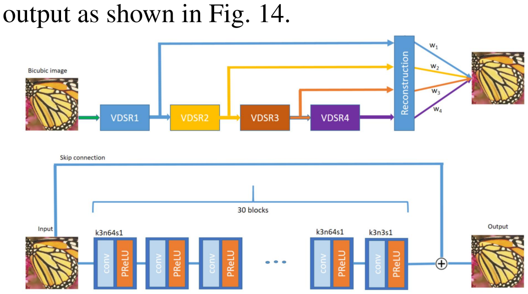


Figure 14. GTY team: multi-fused deep network based on VDSR.

4.10. DL-61-86 A two-stage solution: deblurring then SR of the LR blur-free images. A blind deconvolution method [39] estimated the blur kernel on each train image and the average blur kernel was used for deblurring. After deblurring, a SRResNet [18, 28] learned the mapping to HR using both MSE loss and a perceptual loss. The training employed the cyclical learning rate strategy [29] and inspired by [37] used both train images and re-scaled images to enhance the generality of the model for local structures of different scales in natural images.

4.11. faceall_Xlabs team For Track 1, $\times 2$, a 20 layer VDSR was trained, while for the other settings 9 layers of ResNet structure (see Fig. 15) were trained with a combination of three losses [38].

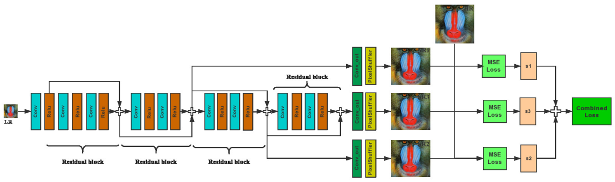


Figure 15. faceall_Xlabs team: proposed net.

4.12. SR2017 team A DNN (similar to VDSR [17]) learns the residual map for the bicubic upscaled input. Since the downscaling operators might be unknown, a multi-scale strategy is employed as commonly used in deblurring methods [30]. Specifically, strided and fractionally-strided convolutional layers are used to downsample and upsample the intermediate feature maps, which exploits multi-scale information and thus helps reconstruct sharper results. In addition, similar with [21] skip links are added to remedy the information loss during the downsampling operation.

4.13. SDQ_SR team SR is seen as a motion prediction problem. The method can be divided into two stages, motion prediction stage and post train stage. (i) For motion prediction stage, a 10 layers VDSR [17] (3×3 kernels, Fig. 16) generated four pixels for each input image pixel then combines them to get the result. (ii) A 10 layers VDSR (5×5 kernels) is used in the post train stage to remove the blocking effects and further improve the final result. The motion prediction and post train strategy are used in unknown down-sampling of $\times 2$ and only motion prediction strategy is used in bicubic down-sampling of $\times 2$.

4.14. HCILab team The VDSR model [17] based on caffe is deployed for the DIV2K dataset. In addition, the solution uses cudnn library for increase in speed and performance. A single model was trained per each challenge track.

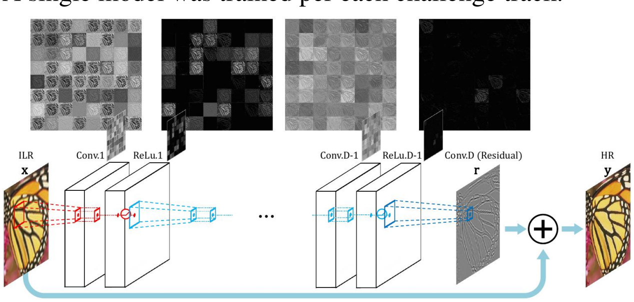


Figure 16. VDSR [17] model based on VGG-16 architecture.

4.15. iPAL team A CNN is implemented to predict the missing details of wavelet coefficients (sub-bands) of the LR images. The network (see Fig. 17) is trained in the wavelet feature domain uniquely with four input and output channels which is named Deep Wavelet Super-Resolution (DWSR) [12]. The input comprises of 4 sub-bands of the LR wavelet coefficients and outputs are residuals (missing details) of 4 sub-bands of HR wavelet coefficients.The output prediction is added to the input to form the final SR wavelet coefficients. Then the inverse 2d discrete wavelet transformation is applied to transform the predicted details and generate the SR results.

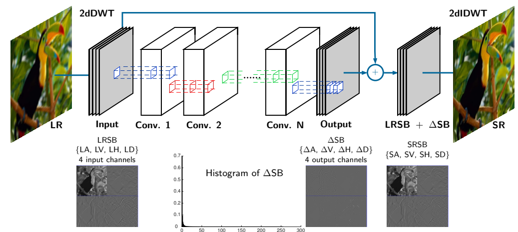


Figure 17. iPAL team: deep wavelet super-resolution.

4.16. WSDSR team WSDSR [7] is an iterative back projection approach (see Fig. 18) which uses as a regularizer a BM3D [8] based filter especially designed for SR. It uses a 1D Wiener filter, as opposed to the more common 3D filter. This difference proved to be crucial to improved performance in SR problems. WSDSR uses self-similarities, no training data, and any real valued scaling factor can be used.

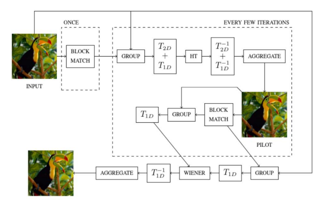


Figure 18. WSDSR team: method diagram.

4.17. Resonance team The solution is based on two cascaded networks. The first deep residual net is used for LR-to-HR upscaling and has inception blocks, skip connections and, instead of deconvolution, employs two PixelShuffle layers [28] for upscaling. The second network, a simple 5-layer convnet with one skip connection from input to output, is used for sharpening/enhancement of the HR image obtained by the first net. First net uses 6, 8, and 10 inception ResNet blocks (see Fig. 10) for $\times 2$, $\times 3$ and $\times 4$.

4.18. zrfanzy team The solution is based on SRResNet [18], uses more layers, a deconv layer, l_1 loss and no batch normalization. The models are trained only for $\times 4$, for $\times 2$ and $\times 3$ the images are upscaled by $\times 4$ and then bicubic downscaled using imresize Matlab function.

4.19. UESTC-kb545 team First, by bicubic interpolation the $\times 2$ image, $\times 4$ image and $\times 4$ sobel boundary image are produced from the unknown downscaled 4x image, then the 3 images are fed into a CNN for two-way fusion of convolution and convolution-transpose, followed by a deep residual net to further regress to the ground truth details.

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