

NCSR: NOISE CONDITIONAL FLOW MODEL FOR LEARNING THE SUPER-RESOLUTION SPACE

Younggeun Kim, Donghee Son

Seoul National University and Deepest

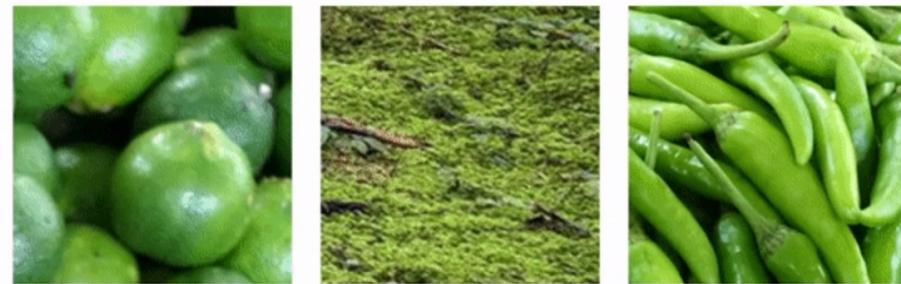


Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.355	27.52	1.871 ₍₁₁₎	-	-
SYSU-FVL	0.244	49.33	8.735 ₍₁₀₎	-	-
nanbeihuishi	0.161	50.46	12.447 ₍₉₎	-	-
FudanZmic21	0.273	47.20	16.450 ₍₇₎	-	-
FutureReference	0.165	37.51	19.636 ₍₆₎	-	-
SR_DL	0.234	39.80	20.508 ₍₅₎	-	-
SSS	0.110	44.70	13.285 ₍₈₎	4.530 ₍₃₎	5.5
BeWater	0.137	49.59	23.948 ₍₃₎	4.720 ₍₄₎	3.5
CIPLAB	0.121	50.70	23.091 ₍₄₎	4.478 ₍₂₎	3.0
njtech&seu	0.149	46.74	26.924 ₍₁₎	4.977 ₍₅₎	3.0
Deepest	0.117	50.54	26.041 ₍₂₎	4.372 ₍₁₎	1.5
SRFlow	0.122	49.86	25.008	4.410	-
ESRGAN	0.124	38.74	0.000	4.467	-
GT	0	∞	-	3.728	-

Table 2. Quantitative comparison of participating teams. (4×)

Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.481	25.55	4.516 ₍₁₀₎	-	-
SYSU-FVL	0.415	47.27	8.778 ₍₉₎	-	-
FudanZmic21	0.496	46.78	14.287 ₍₇₎	-	-
FutureReference	0.291	36.51	17.985 ₍₅₎	-	-
njtech&seu	0.366	29.65	28.193 ₍₁₎	-	-
SSS	0.237	37.43	13.548 ₍₈₎	4.692 ₍₃₎	5.5
SR_DL	0.311	42.28	14.817 ₍₆₎	4.738 ₍₄₎	5.0
BeWater	0.297	49.63	23.700 ₍₃₎	5.133 ₍₅₎	4.0
CIPLAB	0.266	50.86	23.320 ₍₄₎	4.637 ₍₂₎	3.0
Deepest	0.259	48.64	26.941 ₍₂₎	4.630 ₍₁₎	1.5
SRFlow	0.282	47.72	25.582	4.635	-
ESRGAN	0.284	30.65	0	4.323	-
GT	0	∞	-	2.613	-

Table 3. Quantitative comparison of participating teams. (8×)



$$\begin{matrix} \text{[Pixelated Image]} & = & \text{[Smoothed Image]} & = & \text{[Reconstructed Image]} \end{matrix}$$



Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.355	27.52	1.871 ₍₁₁₎	-	-
SYSU-FVL	0.244	49.33	8.735 ₍₁₀₎	-	-
nanbeihuishi	0.161	50.46	12.447 ₍₉₎	-	-
FudanZmic21	0.273	47.20	16.450 ₍₇₎	-	-
FutureReference	0.165	37.51	19.636 ₍₆₎	-	-
SR_DL	0.234	39.80	20.508 ₍₅₎	-	-
SSS	0.110	44.70	13.285 ₍₈₎	4.530 ₍₃₎	5.5
BeWater	0.137	49.59	23.948 ₍₃₎	4.720 ₍₄₎	3.5
CIPLAB	0.121	50.70	23.091 ₍₄₎	4.478 ₍₂₎	3.0
njtech&seu	0.149	46.74	26.924 ₍₁₎	4.977 ₍₅₎	3.0
Deepest	0.117	50.54	26.041 ₍₂₎	4.372 ₍₁₎	1.5
SRFlow	0.122	49.86	25.008	4.410	-
ESRGAN	0.124	38.74	0.000	4.467	-
GT	0	∞	-	3.728	-

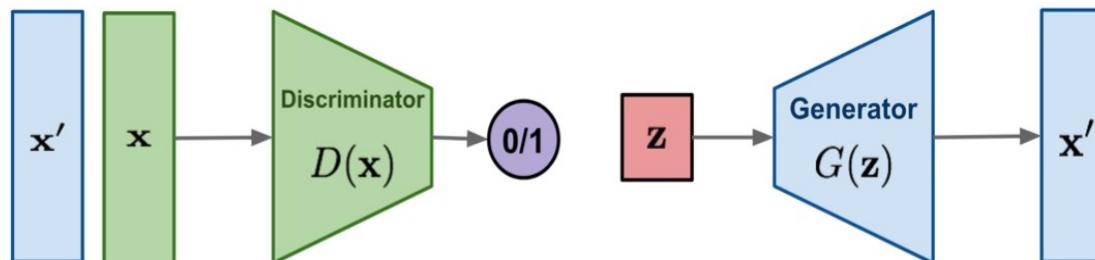
Table 2. Quantitative comparison of participating teams. (4×)

Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.481	25.55	4.516 ₍₁₀₎	-	-
SYSU-FVL	0.415	47.27	8.778 ₍₉₎	-	-
FudanZmic21	0.496	46.78	14.287 ₍₇₎	-	-
FutureReference	0.291	36.51	17.985 ₍₅₎	-	-
njtech&seu	0.366	29.65	28.193 ₍₁₎	-	-
SSS	0.237	37.43	13.548 ₍₈₎	4.692 ₍₃₎	5.5
SR_DL	0.311	42.28	14.817 ₍₆₎	4.738 ₍₄₎	5.0
BeWater	0.297	49.63	23.700 ₍₃₎	5.133 ₍₅₎	4.0
CIPLAB	0.266	50.86	23.320 ₍₄₎	4.637 ₍₂₎	3.0
Deepest	0.259	48.64	26.941 ₍₂₎	4.630 ₍₁₎	1.5
SRFlow	0.282	47.72	25.582	4.635	-
ESRGAN	0.284	30.65	0	4.323	-
GT	0	∞	-	2.613	-

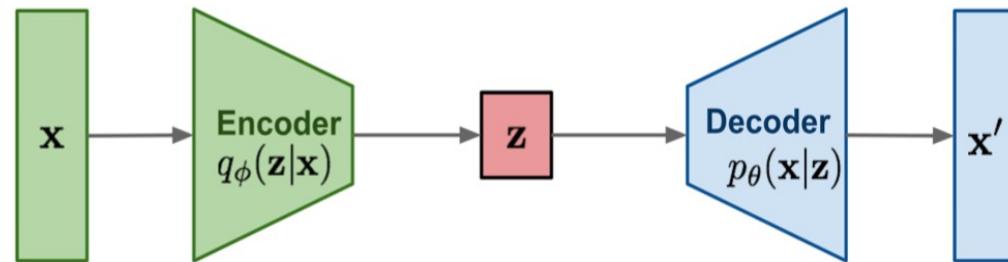
Table 3. Quantitative comparison of participating teams. (8×)



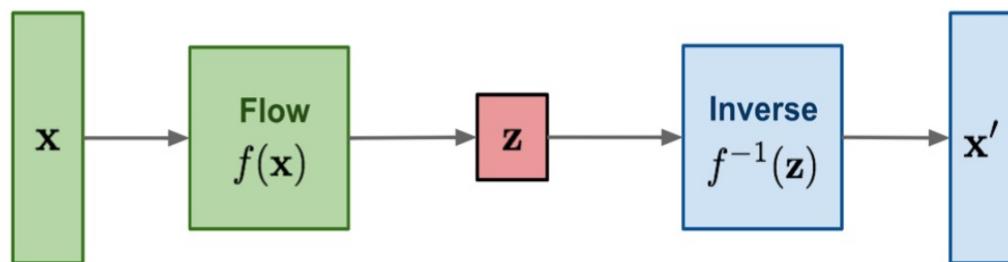
GAN: minimax the classification error loss.



VAE: maximize ELBO.



Flow-based generative models: minimize the negative log-likelihood



-Simple distribution to Complex distribution

-Inverse functions

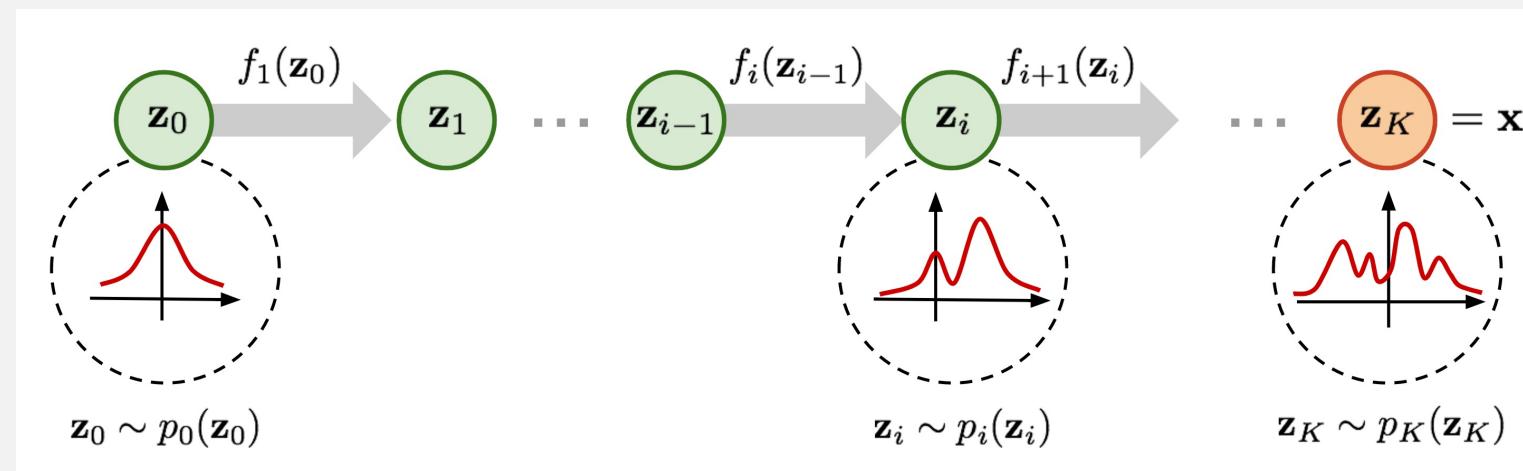
-Not deterministic model



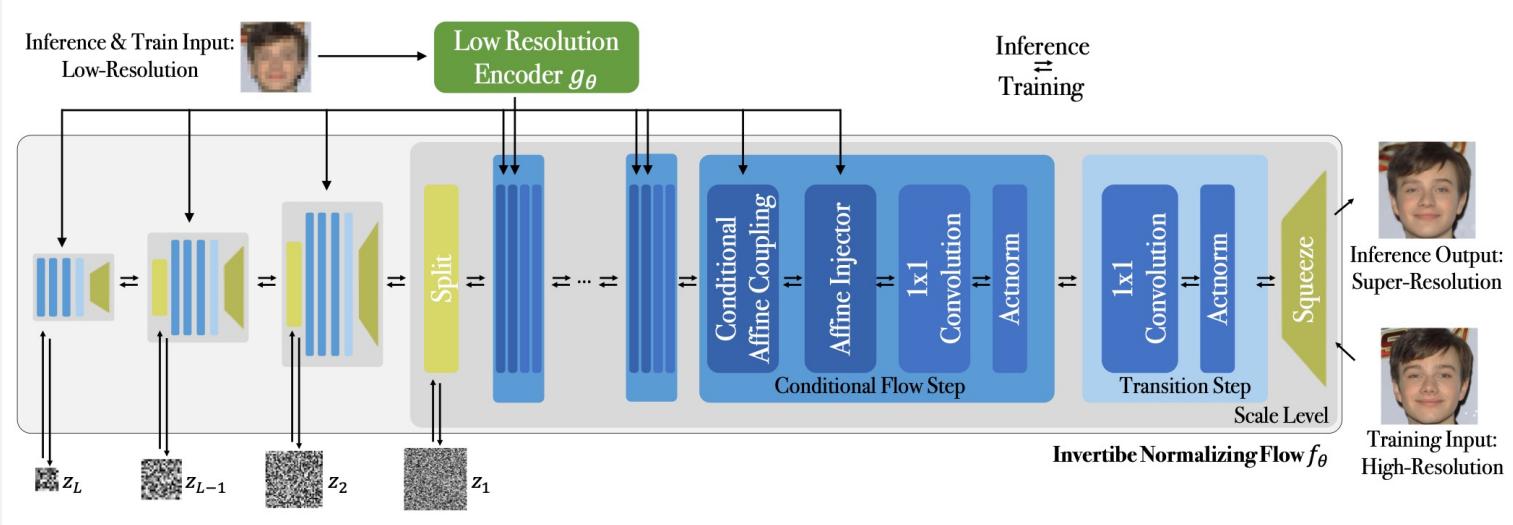
SRFLOW

- SRFlow: Super-Resolution + Normalizing Flow
- Normalizing Flow : Generative model, $P(x|z)$

- $X = z_k = f_k \circ \cdots f_2 \circ f_1(z_0)$
- $\log P(X) = \log \pi_0(z_0) - \sum_{i=1}^k \log |\det \frac{df_i}{dz_{i-1}}|$
 - Function f_i
 - Invertible & easy to compute jacobian determinant



SRFLOW



Normalizing Flow

1. $z_1, z_2 = \text{split}(z)$
2. $\text{scale}, \text{bias} = fn(z_2)$
3. $z_1 = \frac{z_1}{\text{scale}} - \text{bias}$
4. $z_{\text{new}} = \text{concat}(z_1, z_2)$

Conditional Normalizing Flow

1. $z_1, z_2 = \text{split}(z)$
2. $\text{scale}, \text{bias} = fn(z_2, LR_image)$
3. $z_1 = \frac{z_1}{\text{scale}} - \text{bias}$
4. $z_{\text{new}} = \text{concat}(z_1, z_2)$

Affine Injector

1. $\text{scale}, \text{bias} = fn(LR_image)$
2. $z = \frac{z}{\text{scale}} - \text{bias}$





DIV2k 828
LR-PSNR: 21.53



DIV2k 873
LR-PSNR: 24.11

Adding
Noise to generate
Various images



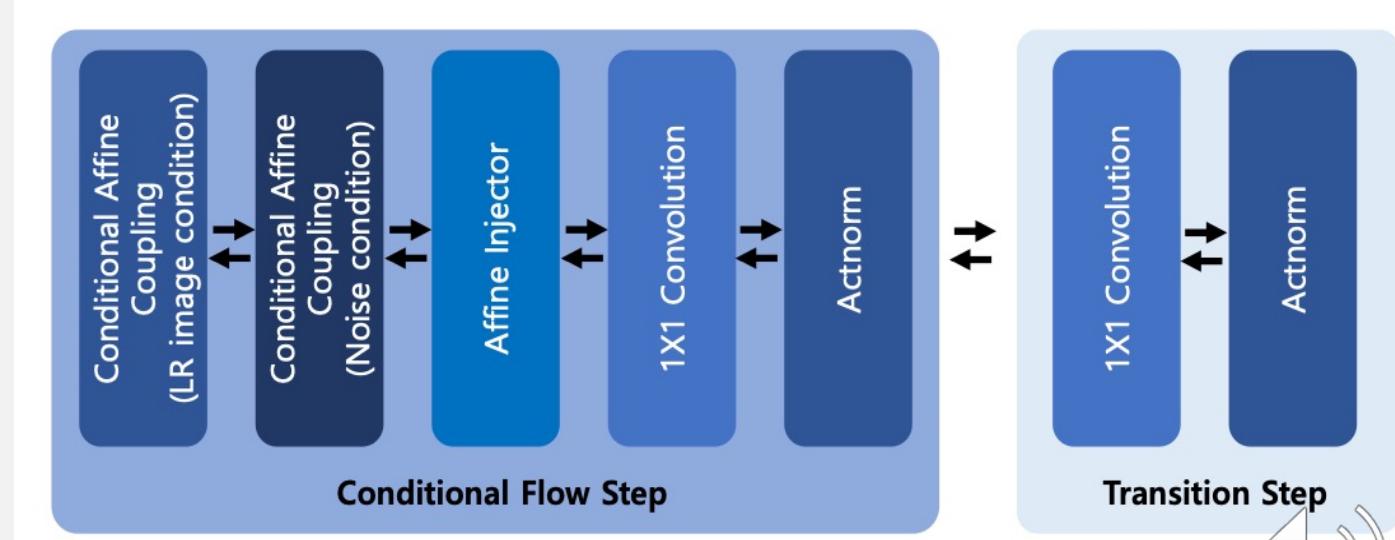


DIV2k 828
LR-PSNR: 21.53



DIV2k 873
LR-PSNR: 24.11

Noise Conditional Layer



Github repo: <https://github.com/younggeun-kim/NCSR>



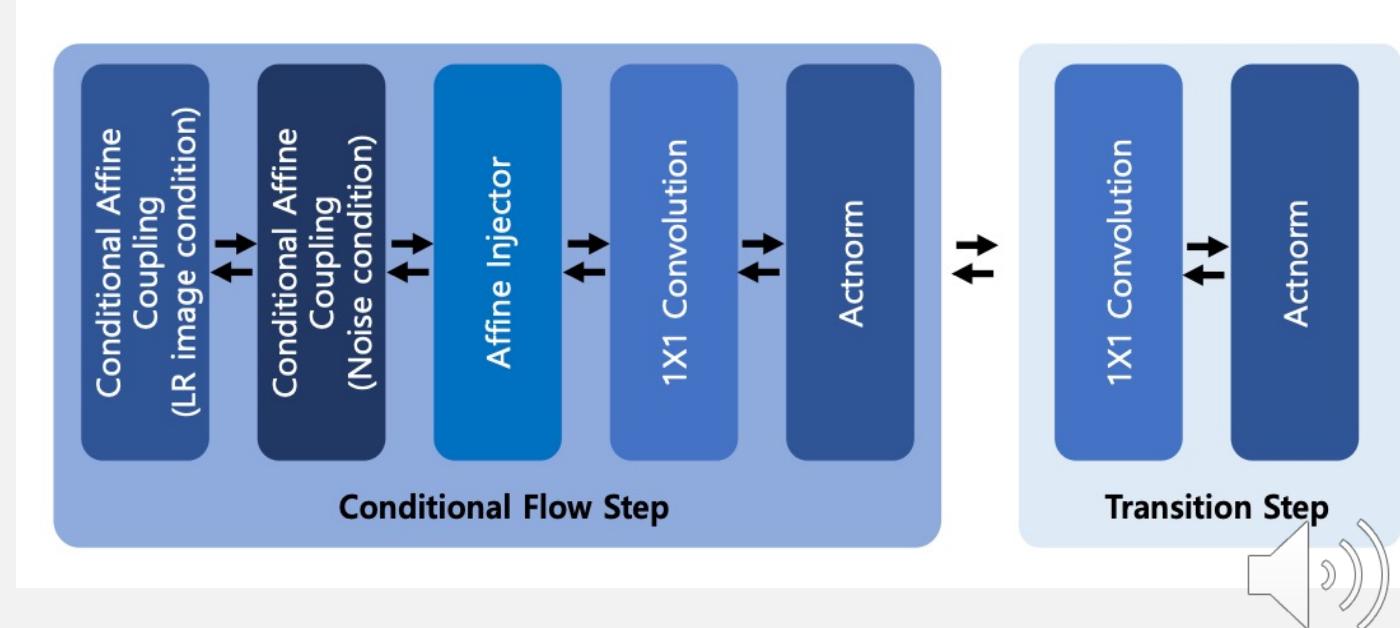


DIV2k 828
LR-PSNR: 21.53



DIV2k 873
LR-PSNR: 24.11

Model	w/o NCL	with NCL
Diversity	25.38	26.72
LPIPS	0.1228	0.1193
LR PSNR	50.08	50.75
LR PSNR-worst	47.32	49.14



NCSR

- Noise Conditional Super-Resolution Model
 - Noise perturbed data
 - Noise Conditional Flow
- 1. Noise sampling
- 2. Data Perturbation
 - $x^+ = x + \nu$ (GT)
 - $y^+ = y + w$ (LR), (w is downsampled ν)
- 3. Noise Conditional Flow
 - $f^{-1}(x^+ | y^+, \nu) = z$

Noise sampling

$$c_i \sim \text{Unif}[a, b]$$

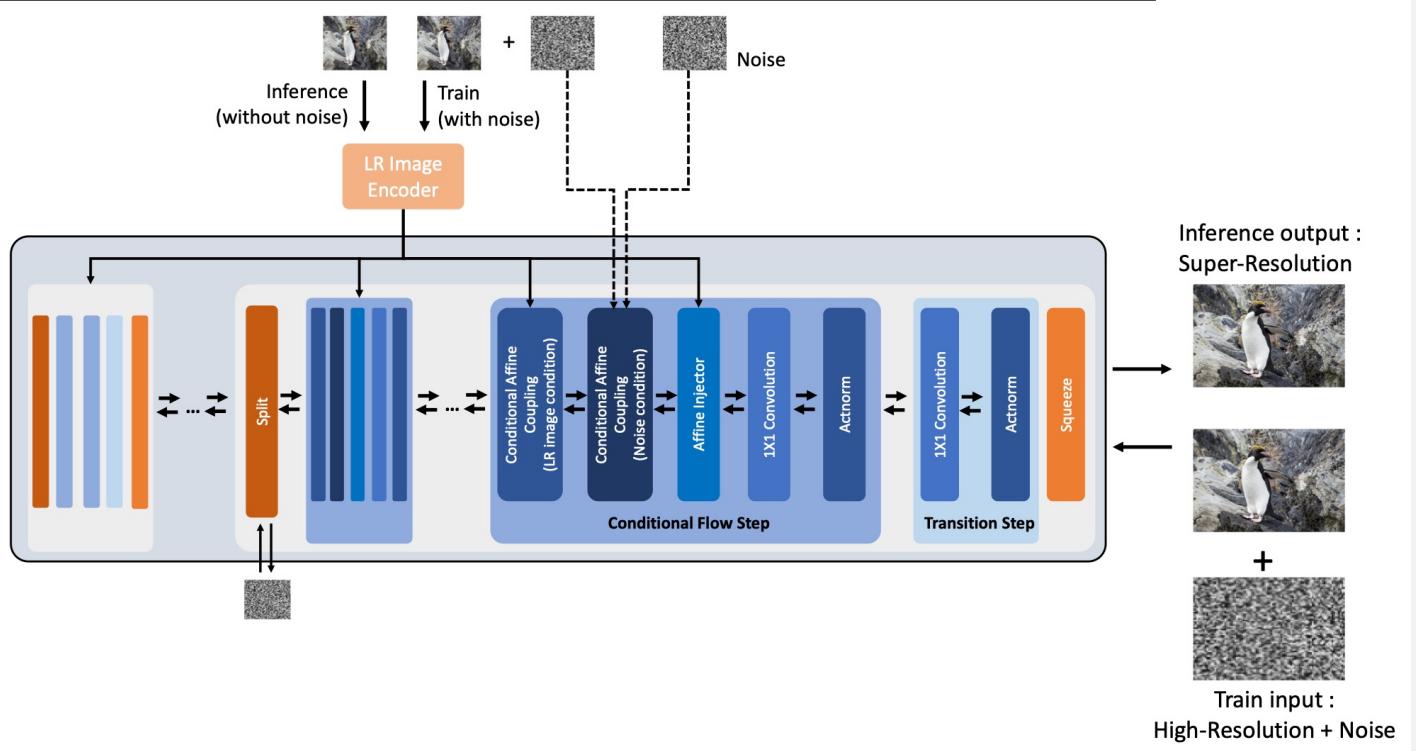
$$\Sigma_i = c_i^2 I$$

$$\nu_i \sim N(0, \Sigma_i)$$



NCSR

- 1. Noise sampling
- 2. Data Perturbation
 - $x^+ = x + v$ (GT)
 - $y^+ = y + w$ (LR)
- 3. Noise Conditional Flow
 - $f^{-1}(x^+|y^+, v) = z$



Normalizing Flow

1. $z_1, z_2 = \text{split}(z)$
2. $\text{scale}, \text{bias} = \text{fn}(z_2)$
3. $z_1 = \frac{z_1}{\text{scale}} - \text{bias}$
4. $z_{\text{new}} = \text{concat}(z_1, z_2)$

Conditional Normalizing Flow

1. $z_1, z_2 = \text{split}(z)$
2. $\text{scale}, \text{bias} = \text{fn}(z_2, y)$
3. $z_1 = \frac{z_1}{\text{scale}} - \text{bias}$
4. $z_{\text{new}} = \text{concat}(z_1, z_2)$

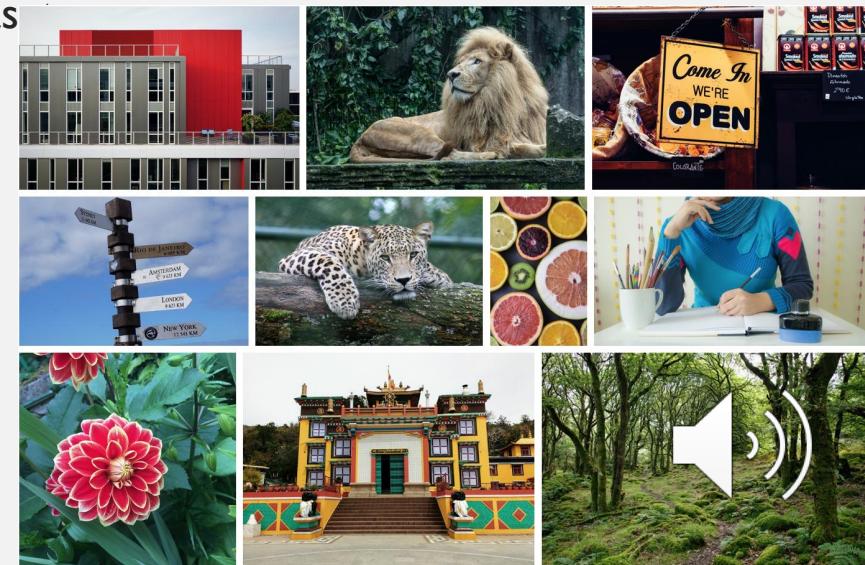
Conditional Normalizing Flow with Noise

1. $z_1, z_2 = \text{split}(z)$
2. $\text{scale}, \text{bias} = \text{fn}(z_2, y^+, v)$
3. $z_1 = \frac{z_1}{\text{scale}} - \text{bias}$
4. $z_{\text{new}} = \text{concat}(z_1, z_2)$



DATASET

- Train data : DF2K
 - 800 + 2650 2K resolution images
- Test / Valid : DIV2K
 - 100 2K resolution images
- Additional Dataset is allowed except DIV2K valid and test datas
 - Unsplash2K
 - Crawled from unsplash.com
 - 498 pairs
 - <http://github.com/dongheehand/unsplash2K>



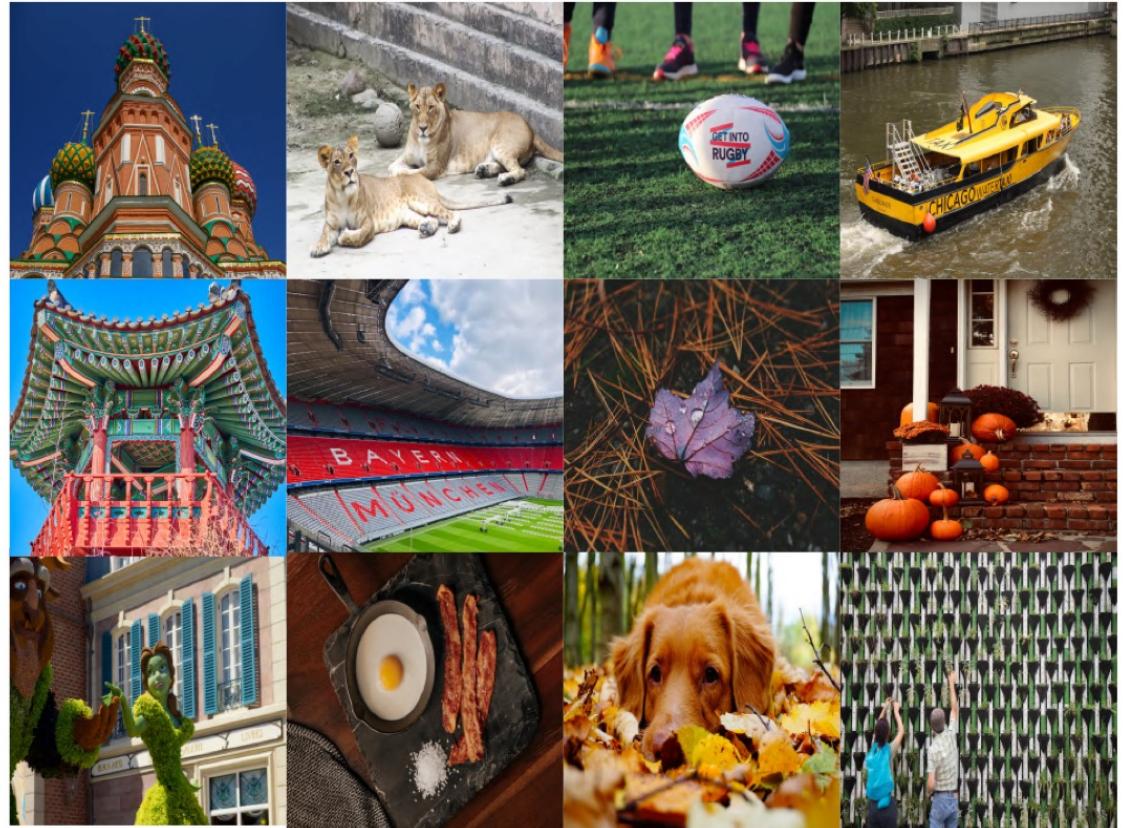


Figure 5: The sample images of Unsplash 2K

New Super Resolution Dataset



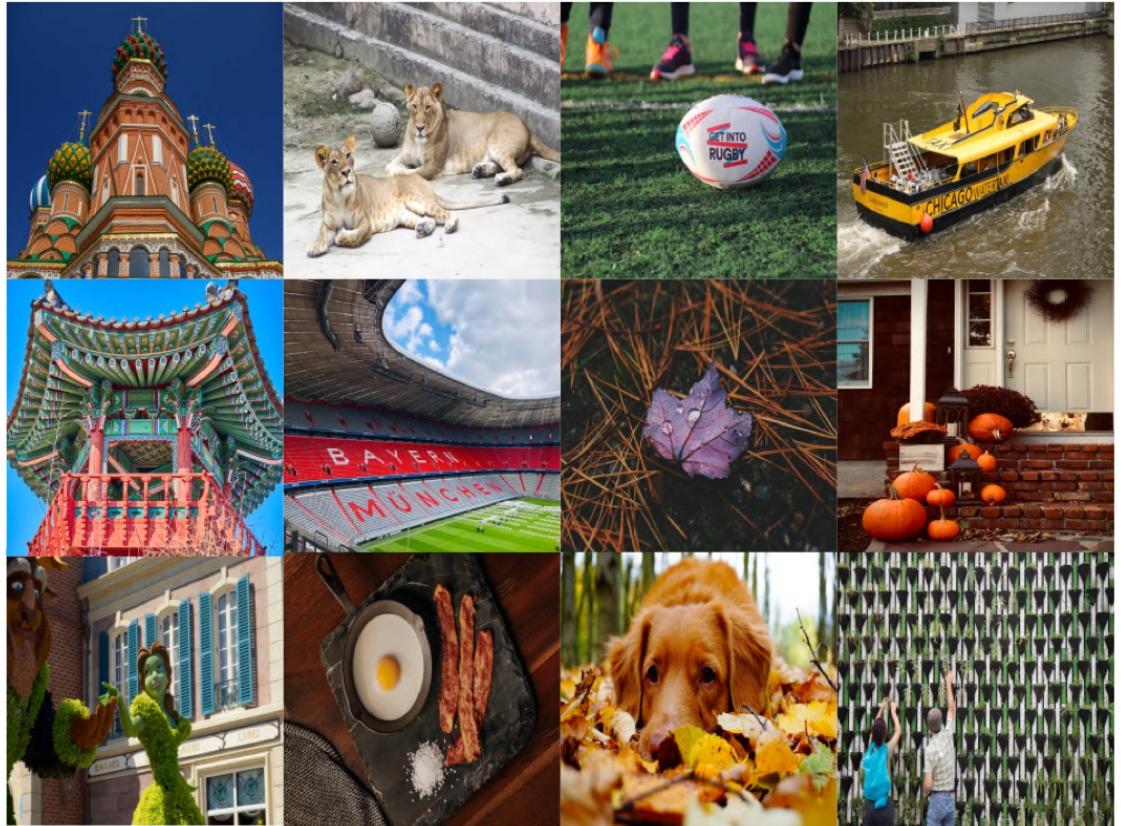


Figure 5: The sample images of Unsplash 2K

New Super Resolution Dataset

Noise Conditional Layer	X	X	✓	✓	✓
Std Conditional Layer	X	✓	X	X	X
Noise-free block	X	✓	X	✓	✓
Add extra data	X	X	X	X	✓
LR-PSNR worst	47.32	45.78	49.01	49.14	50.13

Ablation Study





HR

Bicubic

ESRGAN

SRFlow

NCSR (Ours)





HR

Bicubic

ESRGAN

SRFlow

NCSR (Ours)

Model	Diversity	LPIPS	LR PSNR
RRDB [28]	0	0.253	49.20
ESRGAN [28]	0	0.124	39.03
ESRGAN+ [26]	22.13	0.279	35.45
SRFlow [22]	25.26	0.120	49.97
NCSR (Ours)	26.72	0.119	50.75
NCSR* (Ours)	26.79	0.118	50.88

Table 1: General image SR $\times 4$ results on the 100 validation images of the DIV2K dataset



Model	Diversity	LPIPS	LR PSNR
RRDB [28]	0	0.253	49.20
ESRGAN [28]	0	0.124	39.03
ESRGAN+ [26]	22.13	0.279	35.45
SRFlow [22]	25.26	0.120	49.97
NCSR (Ours)	26.72	0.119	50.75
NCSR* (Ours)	26.79	0.118	50.88

Model	Diversity	LPIPS	LR PSNR
RRDB [28]	0	0.419	45.43
ESRGAN [28]	0	0.277	31.35
SRFlow [22]	25.31	0.272	50.00
NCSR (Ours)	26.8	0.278	44.55
NCSR* (Ours)	25.7	0.253	49.97

Table 2: General image SR $\times 8$ results on the 100 validation images of the DIV2K dataset



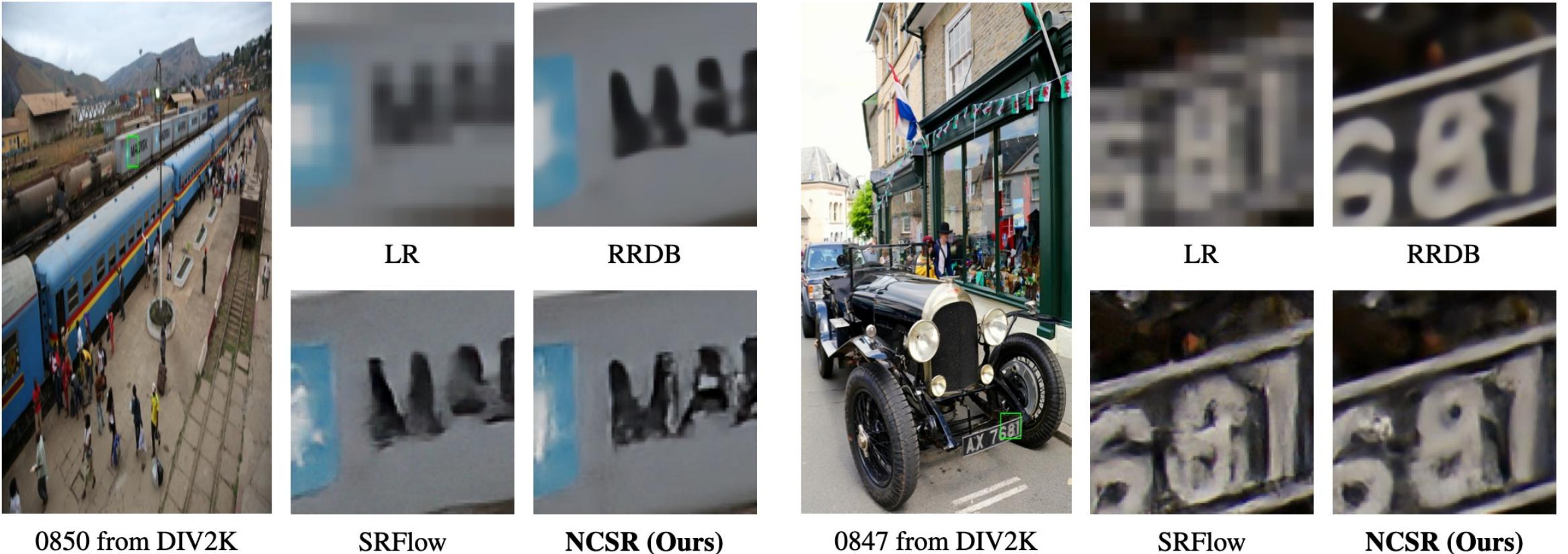


Figure 6: Qualitative comparisons with other methods for $\times 8$ SR model.



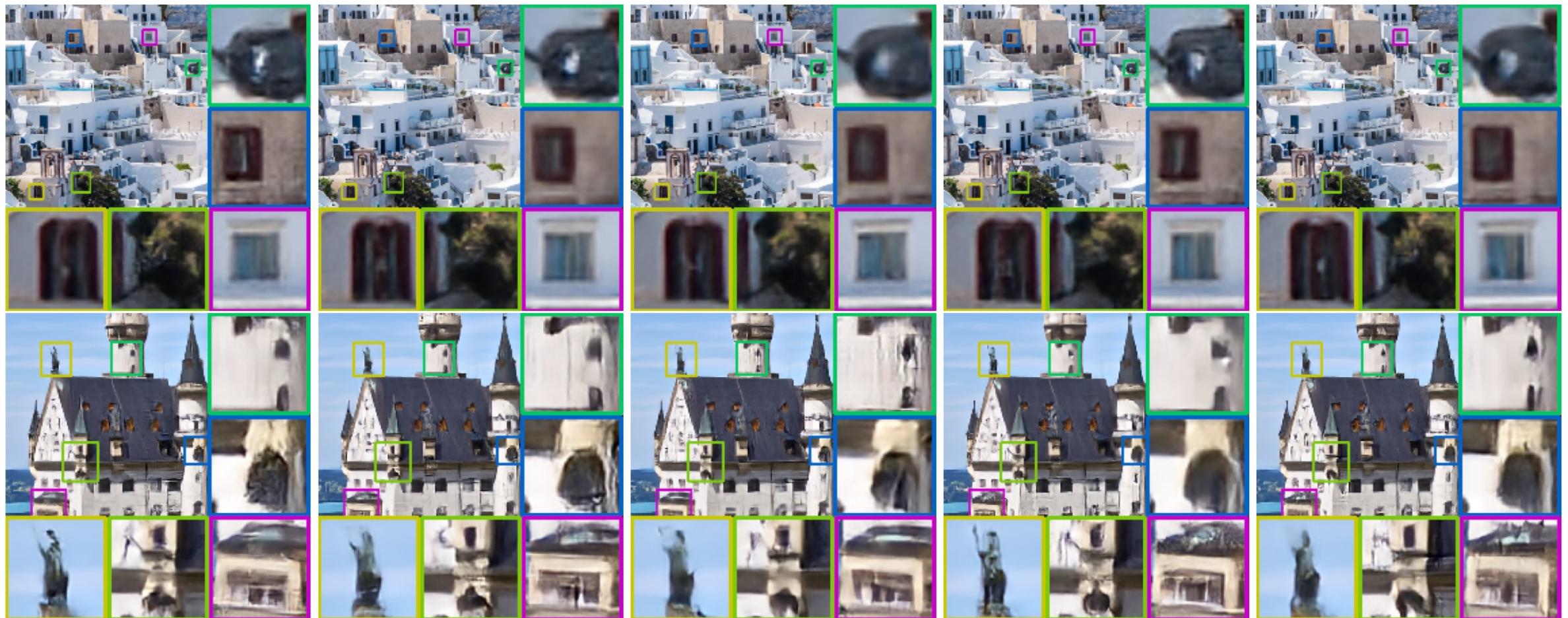


Figure 7: Random samples generated by NCSR. Upper : $\times 4$ SR model, Lower : $\times 8$ SR model



X4 task



Figure 2. Qualitative comparison between the participating approaches for 4× super-resolution

X8 task

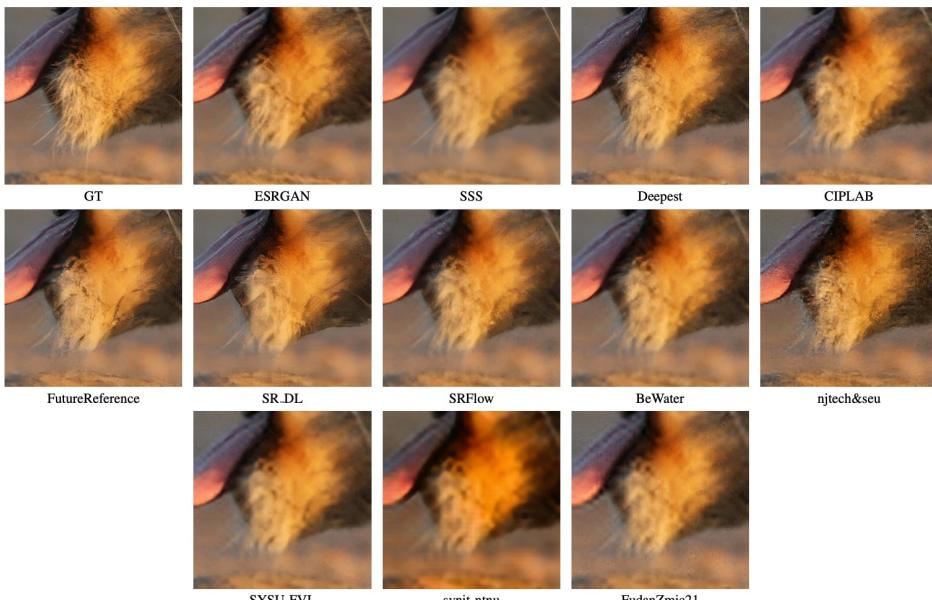


Figure 3. Qualitative comparison between the participating approaches for 8× super-resolution

Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.355	27.52	1.871 ₍₁₁₎	-	-
SYSU-FVL	0.244	49.33	8.735 ₍₁₀₎	-	-
nanbeihuishi	0.161	50.46	12.447 ₍₉₎	-	-
FudanZmic21	0.273	47.20	16.450 ₍₇₎	-	-
FutureReference	0.165	37.51	19.636 ₍₆₎	-	-
SR_DL	0.234	39.80	20.508 ₍₅₎	-	-
SSS	0.110	44.70	13.285 ₍₈₎	4.530 ₍₃₎	5.5
BeWater	0.137	49.59	23.948 ₍₃₎	4.720 ₍₄₎	3.5
CIPLAB	0.121	50.70	23.091 ₍₄₎	4.478 ₍₂₎	3.0
njtech&seu	0.149	46.74	26.924 ₍₁₎	4.977 ₍₅₎	3.0
Deepst	0.117	50.54	26.041 ₍₂₎	4.372 ₍₁₎	1.5
SRFlow	0.122	49.86	25.008	4.410	-
ESRGAN	0.124	38.74	0.000	4.467	-
GT	0	∞	-	3.728	-

Table 2. Quantitative comparison of participating teams. (4×)

Team	LPIPS	LR-PSNR	Div. Score S_{10} [%]	MOR	Final Rank
svnit_ntnu	0.481	25.55	4.516 ₍₁₀₎	-	-
SYSU-FVL	0.415	47.27	8.778 ₍₉₎	-	-
FudanZmic21	0.496	46.78	14.287 ₍₇₎	-	-
FutureReference	0.291	36.51	17.985 ₍₅₎	-	-
njtech&seu	0.366	29.65	28.193 ₍₁₎	-	-
SSS	0.237	37.43	13.548 ₍₈₎	4.692 ₍₃₎	5.5
SR_DL	0.311	42.28	14.817 ₍₆₎	4.738 ₍₄₎	5.0
BeWater	0.297	49.63	23.700 ₍₃₎	5.133 ₍₅₎	4.0
CIPLAB	0.266	50.86	23.320 ₍₄₎	4.637 ₍₂₎	3.0
Deepst	0.259	48.64	26.941 ₍₂₎	4.630 ₍₁₎	1.5
SRFlow	0.282	47.72	25.582	4.635	-
ESRGAN	0.284	30.65	0	4.323	-
GT	0	∞	-	2.613	-

Table 3. Quantitative comparison of participating teams. (8×)



SUMMARY

- Flow-based model(not deterministic model)
- Noise adding to generate diverse super resolution images
- Noise conditional layer to inform noise to model
- Solving dimension mismatch leads good perceptual quality
- Got 1st place in NTIRE 2021, Learning for the Super Resolution task both of X4, X8 tasks.
- Github repo: <https://github.com/younggeun-kim/NCSR>
- If you have question about paper or presentation, please send mail to eyfydsyd97@snu.ac.kr

