1. Supplementary Material

1.1. Optimal hyperparameters from Bayesian sweep

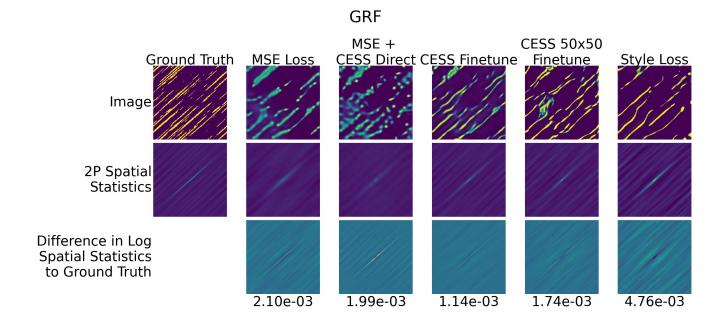
	MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Learning Rate	7.3×10^{-5}	2.5×10^{-4}	5.1×10^{-5}	4.8×10^{-5}	1.2×10^{-4}
Depth	4	3	4	4	4
CESS Loss Weight	0	2.3×10^{3}	6.3×10^{3}	5.2×10^{3}	4.5×10^{-3}
Gradient Clipping	1	0.1	1	1	0.1

Table 1. Best hyperparameters for each model as determined by a Bayesian sweep. For the MSE + CESS model, the weight of MSE loss was fixed at 1×10^{-3} .

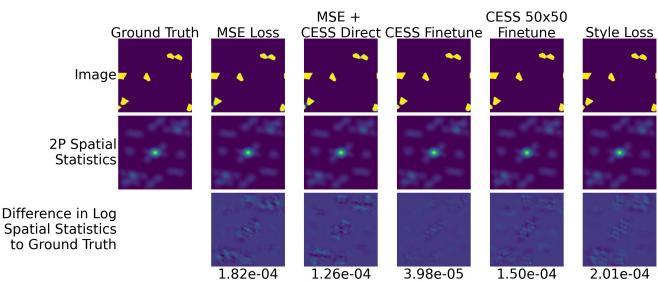
1.2. Reconstructions of a sample from each class with spatial statistics comparison

Qualitative analysis can be seen in the next section.

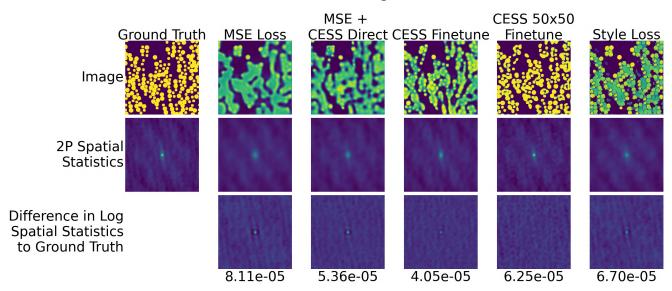
VoronoiSmall MSE + CESS 50x50 Ground Truth **MSE Loss** CESS Direct CESS Finetune Finetune Style Loss **Image** 2P Spatial Statistics Difference in Log **Spatial Statistics** to Ground Truth 2.91e-04 2.09e-04 8.06e-05 2.07e-04 2.40e-04



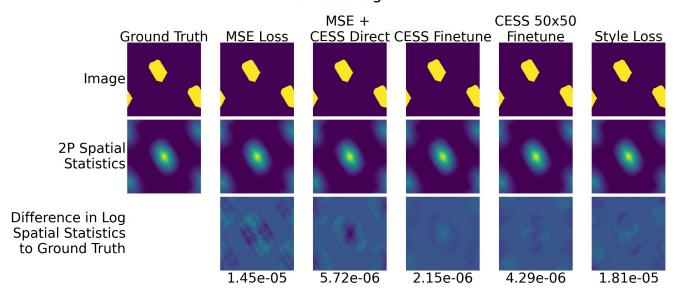
Voronoi Medium Spaced



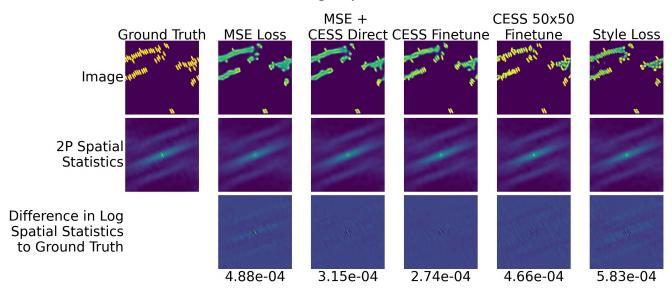
VoidSmallBig



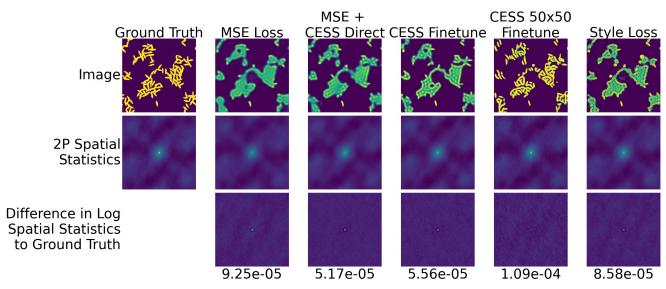
VoronoiLarge



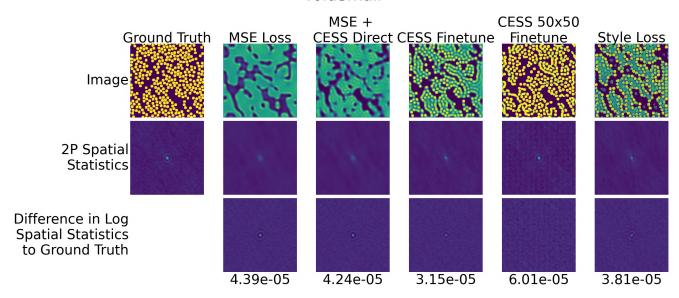
AngEllipse



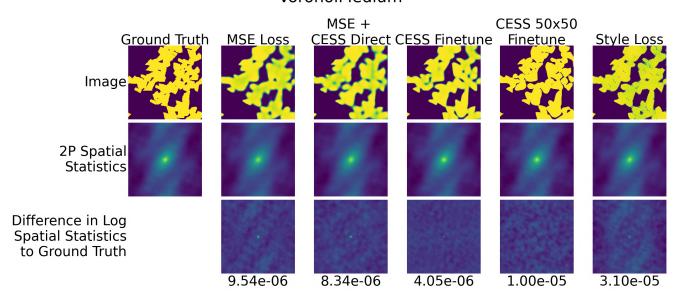
Random Ellipse



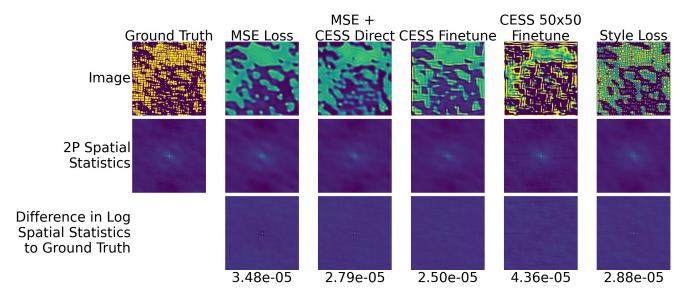
VoidSmall



VoronoiMedium

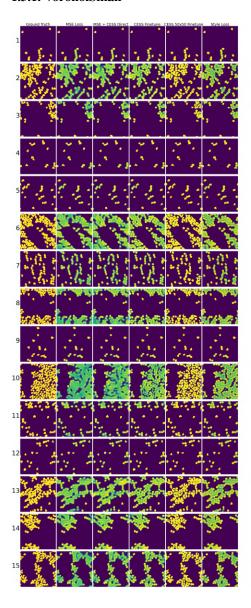


NBSA



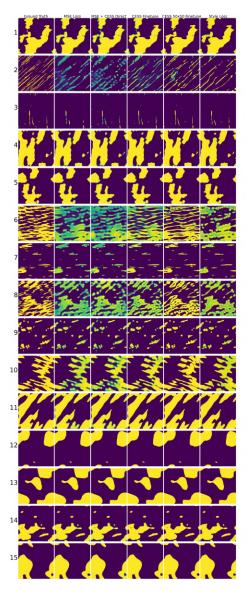
1.3. Qualitative assessment of reconstructions of samples from each class

1.3.1. VoronoiSmall



MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Good reconstructions	Slightly sharper recon-	Similar to MSE + CESS;	Reconstructions are	Much better at preserv-
for relatively sparse mi-	structions compared to	has sharper reconstruc-	much sharper, but polyg-	ing polygonal nature of
crostructures, but grains	MSE, but similar prob-	tions compared to MSE	onal nature of grains is	grains, but still has is-
still often rounded into	lems with grain detail.	but still often recon-	not well preserved, with	sues with rounding their
blurry, circular blobs.		structs grains as circular	grains in reconstruction	corners.
		blobs rather than poly-	essentially completely	
		gons	rounded.	

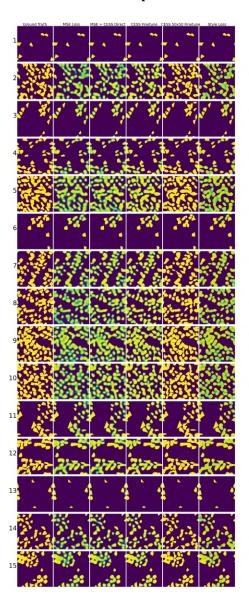
1.3.2. GRF



Microstructures in this class are somewhat diverse, as the classification refers to the generation technique (Gaussian Random Field) and not inherently to any visual similarity.

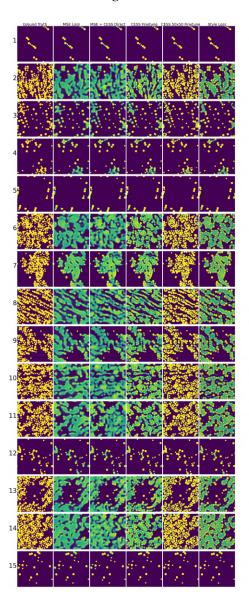
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Reconstructs images	Similar to MSE; slightly	Slightly better recon-	Better reconstructions,	Reconstructions are gen-
with large, smooth blobs	better resolution of fine	structions for some	and image is almost	erally good, but often
well. Does poorly on	detail, although some-	images (Image 2).	entirely binary. Does	hallucinate existence of
images with fine detail,	times reconstructs lines	Sometimes hallucinates	not hallucinate grains	polygonal grains (Im-
generally reconstructing	as series of blobs (Image	existence of grains (Im-	as strongly (Image 8).	ages 6, 7, and 8). Line
them blurrily.	2)	age 8).	Reconstructions some-	like microstructures
-			times introduce artifacts	still lack some detail in
			(Image 2), and line like	streaks (Image 2).
			microstructures do not	
			contain all streaks.	

1.3.3. VoronoiMediumSpaced



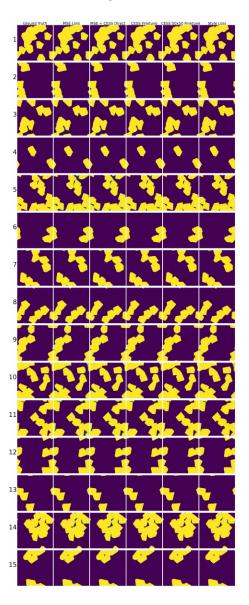
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Good reconstructions	Slightly sharper recon-	Similar to MSE + CESS;	Reconstructions are	Slightly better at pre-
for relatively sparse	structions compared to	has sharper reconstruc-	much sharper, but polyg-	serving polygonal nature
microstructures. Denser	MSE, but similar prob-	tions compared to MSE	onal nature of grains is	of grains, but still has is-
microstructures have	lems with grain detail.	but still sometimes	not well preserved, with	sues with rounding their
blurry reconstructions,		reconstructs grains as	grains in reconstruction	corners.
and grain detail is lost,		blurry blobs	generally rounded.	
often represented instead				
as blurry circles.				

1.3.4. VoidSmallBig



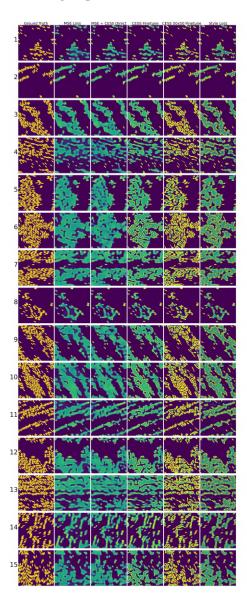
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Good reconstructions for	Slightly better grain	Much better grain res-	Much sharper recon-	Preserves grain structure
sparse microstructures.	reconstruction compared	olution compared to	structions. Sometimes	the best, but image is not
Denser microstructures	to MSE, but similar	MSE and MSE+CESS,	incorrectly reconstructs	binary
have blurry reconstruc-	problems with blurring.	but still has some issues	groups of grains as	-
tions, with groups of		with blurring for dense	streaks (Image 8). Some	
grains blurring into large		microstructures.	circular grains also	
blobs.			become ellipses (Images	
			3, 4)	

1.3.5. VoronoiLarge



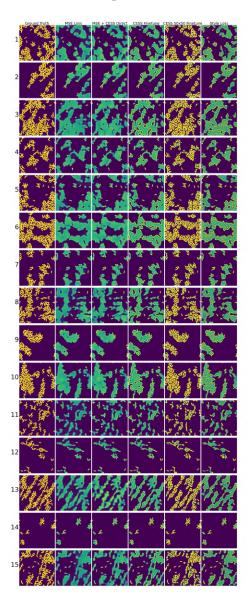
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Good reconstructions,	Very similar to MSE,	Much less blurring near	No blurring, but corners	Very similar to CESS
but slight blurring near	with same blurring issue	edges compared to MSE	of polygonal grains are	finetuned on 50x50 crop;
edges of grains.	near grain edges.	and MSE+CESS.	sometimes rounded (Im-	has similar problems
			age 10)	with rounding of polyg-
				onal grains.

1.3.6. AngEllipse



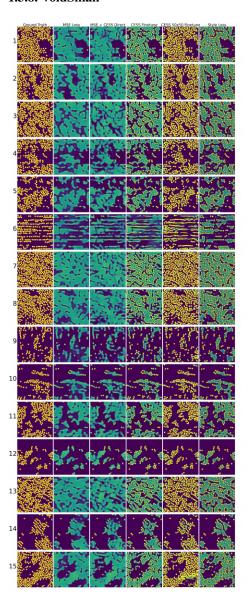
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Reconstructions are	Similar to MSE, al-	Slightly clearer resolu-	Much clearer resolution	Very clear resolution of
poor, generally blurring	though slightly better	tion of grains, but el-	of elliptical grains, but	elliptical grains, with
large areas of grains into	resolution of grains in	liptical nature is still	not consistently oriented	consistent orientation.
a single blob.	blobs, although elliptical	not prominent and some-	in one direction	However, often hal-
	nature of grains is not	times hallucinates exis-		lucinates existence of
	evident.	tence of circular grains		circular grains (Images
		(Image 6)		1, 2, 6, 12, 13)

1.3.7. RandomEllipse



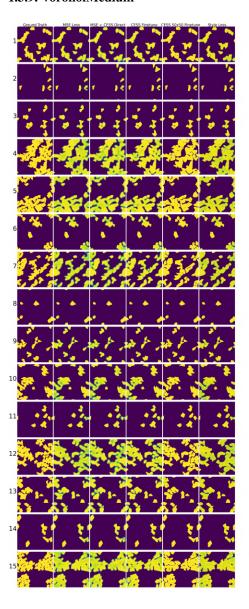
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Reconstructions are	Similar to MSE. Slight	Slightly clearer resolu-	Much clearer resolution	Unclear resolution of el-
poor, generally blurring	resolution of grains in	tion of grains, but el-	of elliptical grains, but	liptical grains, instead
large areas of grains into	blobs, but often as cir-	liptical nature is still	dense sections of grains	producing more polygo-
a single blob.	cular grains and not el-	not prominent and some-	sometimes merge.	nal like grain structures.
	lipses.	times hallucinates exis-	'	
	'	tence of circular grains	'	
		(Images 5, 11)		

1.3.8. VoidSmall



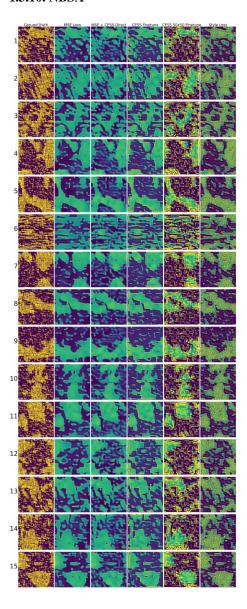
Mar	NOT OFFICE	GEGG E	GEGG 50 50 F	l G. 1 T
MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Generally unrealistic	Generally unrealistic,	Somewhat realistic.	Grains are essentially	Reconstructions com-
reconstructions; closely	but some grain structure	Grains are mostly	completely resolved and	pletely preserve grain
packed grains are recon-	is now visible in the	resolved in blobs, al-	image is almost entirely	structure, but image
structed as a blurry blob.	blobs.	though some blurriness	binary. Lines of grains	is not binary and has
		is still present. Lines	are still merged into	variable weight for each
		of grains are sometimes	linear streaks (Image 6)	grain.
		incorrectly merged in		
		the reconstruction into		
		linear streaks (Image 6).		

1.3.9. VoronoiMedium



MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Sparse regions are re-	Slightly better resolution	Slightly better resolution	Image is much sharper	Best preserves the
constructed well, but	in blurry blob regions,	than MSE+CESS, but	but faces the same prob-	polygonal structure of
dense regions of grains	but still faces essentially	polygonal nature of	lem as CESS Finetune in	grains.
are merged into blurry	the same issues as MSE.	grains is sometimes	preserving polygonal na-	
blobs		not present in recon-	ture of grains.	
		structions, which have		
		rounded corners		

1.3.10. NBSA



MSE	MSE + CESS	CESS Finetune	CESS 50x50 Finetune	Style Loss
Poor reconstructions;	Slightly better resolution	Slight resolution of	Poor reconstructions,	Preserves the square like
grain structure not	in blurry regions, but	grains at corners as	with few grains preserv-	nature of grains very
present, with regions	grains resolved as cir-	square-like, but for the	ing square-like nature	well.
being represented as	cular grains rather than	most part grains are	and instead mostly	
blurry blobs.	square-like grains.	merged into lines.	merging into lines.	

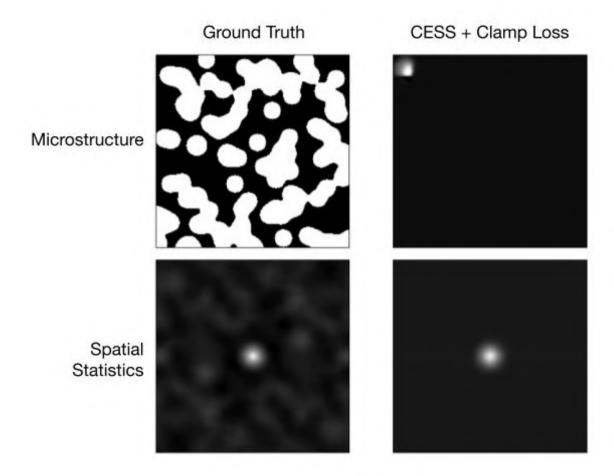


Figure 1. Results from training with only CESS and clamp loss.

1.4. Hypothetical explanation for poor training behaviour of CESS

We first visualized an approximate loss landscape. Two synthetic circle microstructures with 5 circles were first generated; a smooth path was then generated between them by interpolating the circle locations. This roughly represents the shortest path between these microstructures in the "ground truth" latent space. The loss between the first microstructure and evenly spaced interpolants from the path were then computed and plotted (Fig 2).

The generated landscapes led us to hypothesize that the CESS loss has many local minima when far from the original microstructure. We additionally hypothesize that this is because there are many microstructures that satisfy the binary constraint and have similar spatial statistics (Fig. 3).

Three main variants of the loss and training procedure were tried to solve this issue, with some justification:

- Training a model with a linear combination of MSE on the microstructure and CESS; MSE dominates when far from the original microstructure, so this has the effect of smoothing out the loss in those regions.
- Finetuning a model trained with MSE on CESS; this would hopefully mean that reconstructions are already close to the original, making CESS more stable
- Finetuning a model trained with MSE on a variant of CESS that only looked at the center 50x50 crop of spatial statistics; this would ideally make the loss focus more on local properties (e.g. grain size, shape) and be less sensitive to global changes.

Models were also trained with MSE and with a mixture of MSE and Style Loss to be used as baselines.

The approximate impact of these methods to the loss landscape is visualized in Fig. 4; overall, the results show that these methods would theoretically remove local extrema and generally smooth the loss landscape.

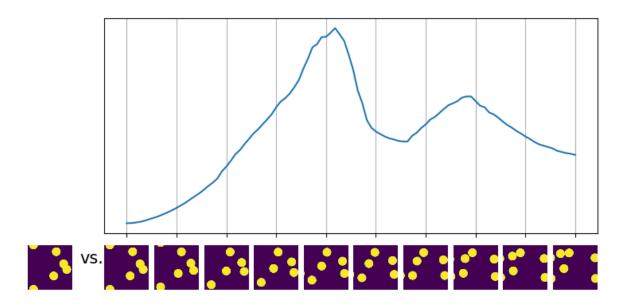


Figure 2. Approximate loss landscape of CESS. Loss is computed vs. the image on the far left of the x-axis.

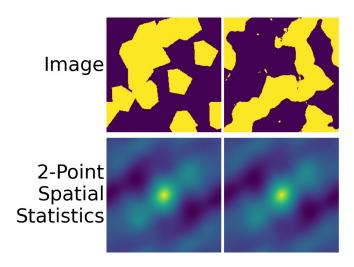


Figure 3. Two different binary images with highly similar spatial statistics.

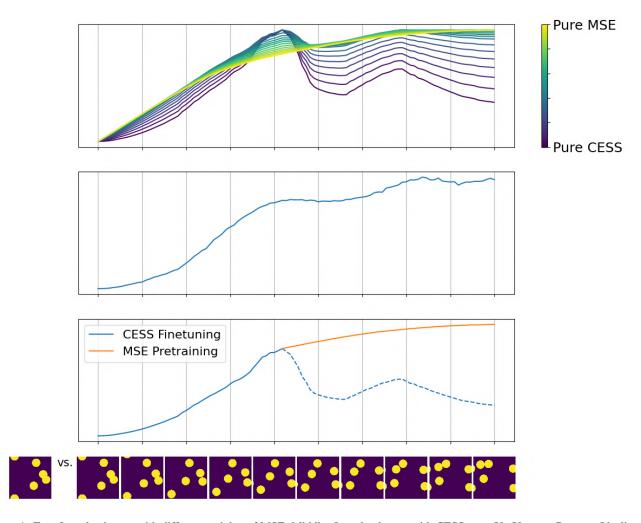


Figure 4. Top: Loss landscape with different weights of MSE. Middle: Loss landscape with CESS on a 50x50 crop. Bottom: Idealized loss landscape using finetuning.

1.5. Network architecture

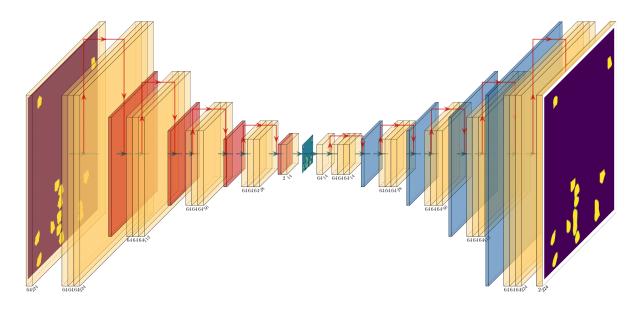


Figure 5. Architecture diagram for model with depth 1. Yellow layers are convolutions, red layers are pooling, and blue layers are upsampling. A ReLU activation is assumed to follow every convolution layer.