Scale-space Tokenization for Improving the Robustness of Vision Transformers

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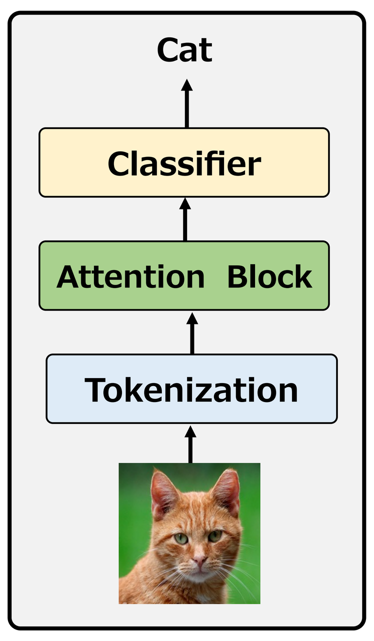
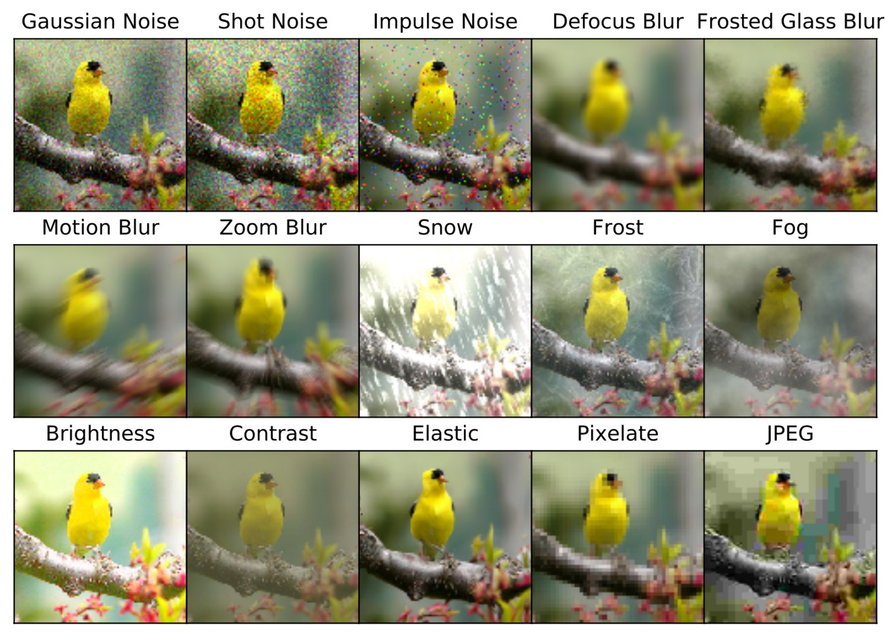
Introduction

The performance of the Vision Transformer (ViT) model and its variants in most vision tasks has surpassed traditional CNNs in terms of in-distribution accuracy. However, ViTs still have significant room for improvement in their robustness to input perturbations.

Robustness benchmark
Adversarial robustness: FGSM [Goodfellow+ 15], PGD [Madry+ 19]
Out-of-distribution robustness: ImageNet-C [Hendrycks+ 19]



ViT model

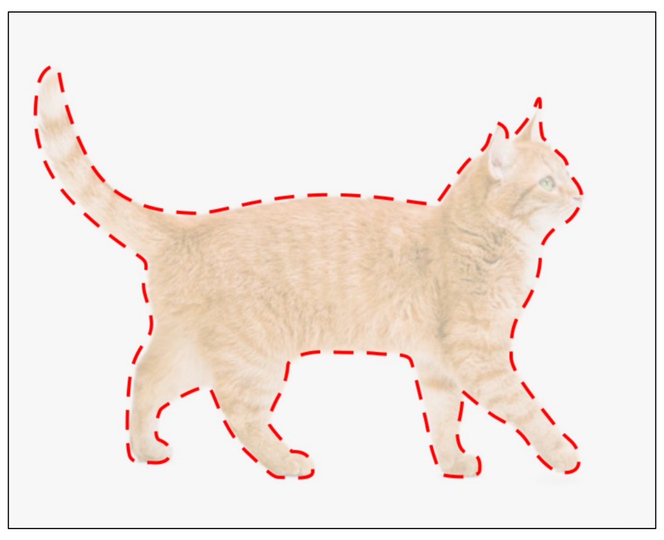


Robustness benchmark

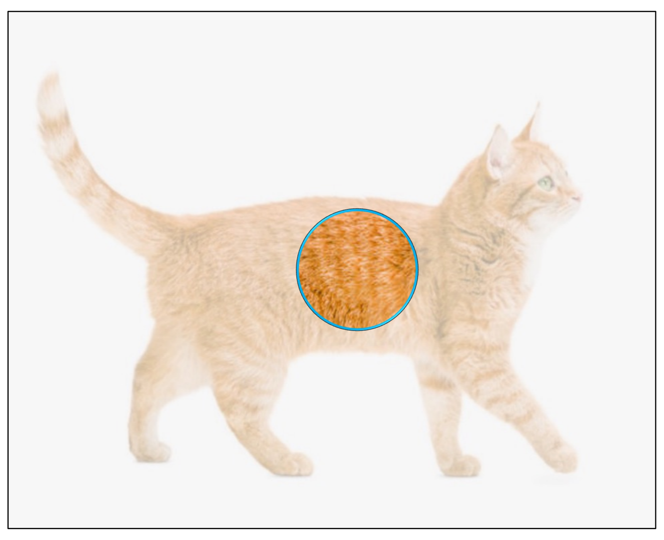
Proposed Method: Scale-space Tokenization for Vision Transformer Models

We propose scale-space tokenization for improving the robustness of vision transformers. Our key idea is to increase shape bias and predispose vision transformers to strike a certain degree of balance between the learning of texture-based and shape-based features by the fine-to-coarse image structures characterized by the scale space.

Motivation: Shape bias and texture bias

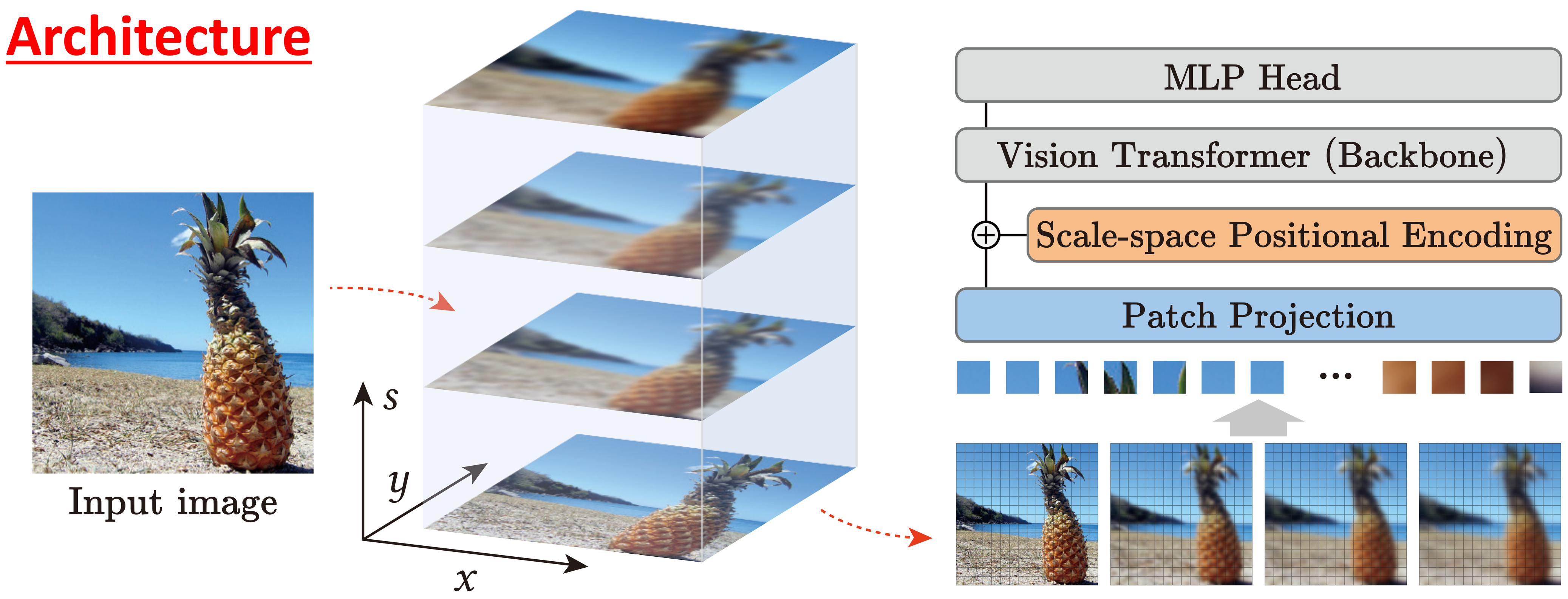


Shape bias

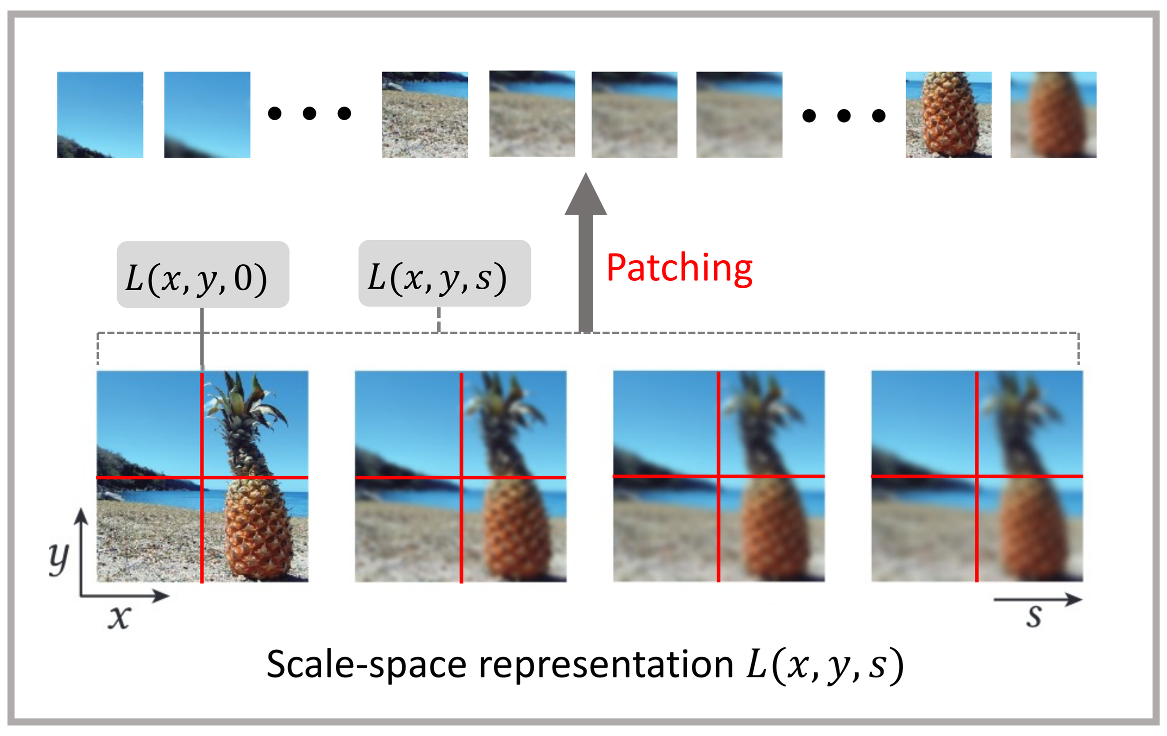


Texture bias

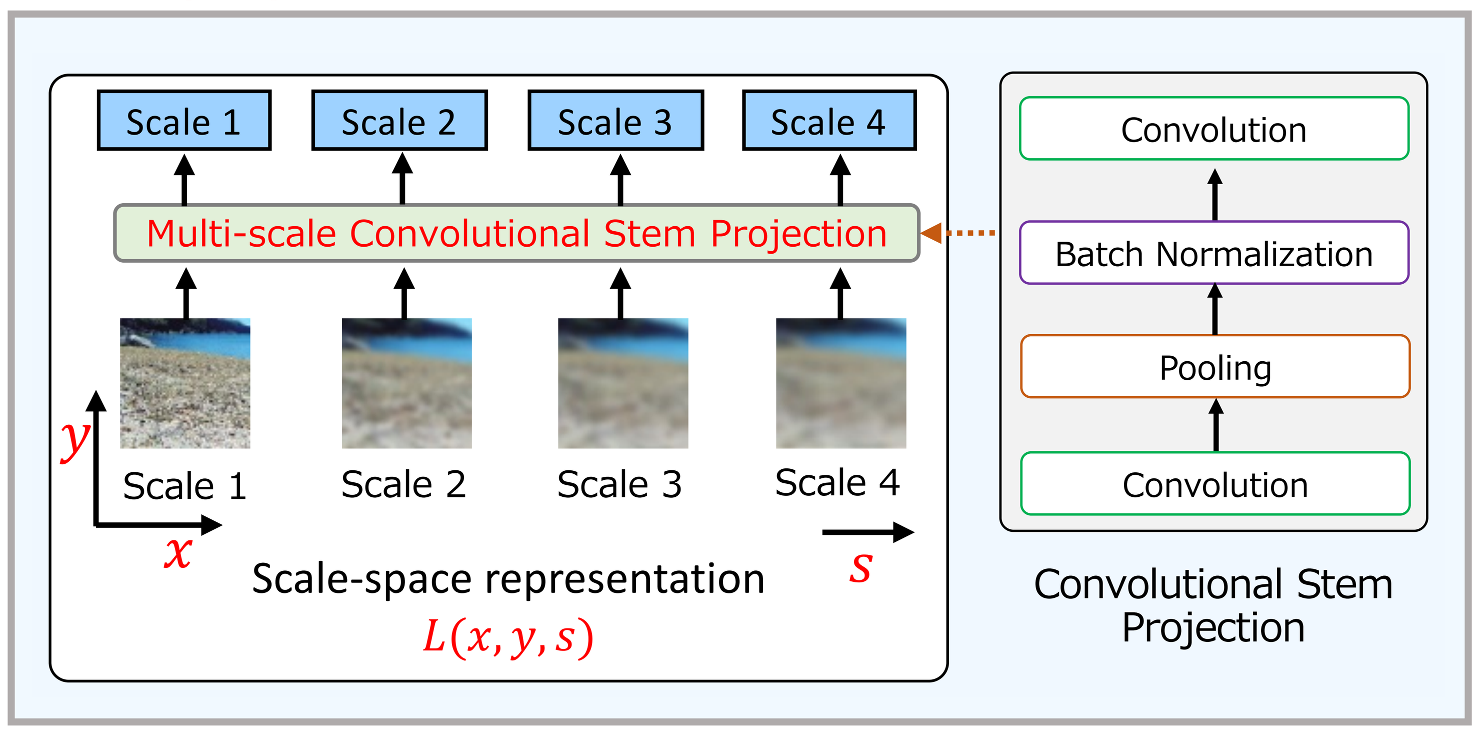
Architecture



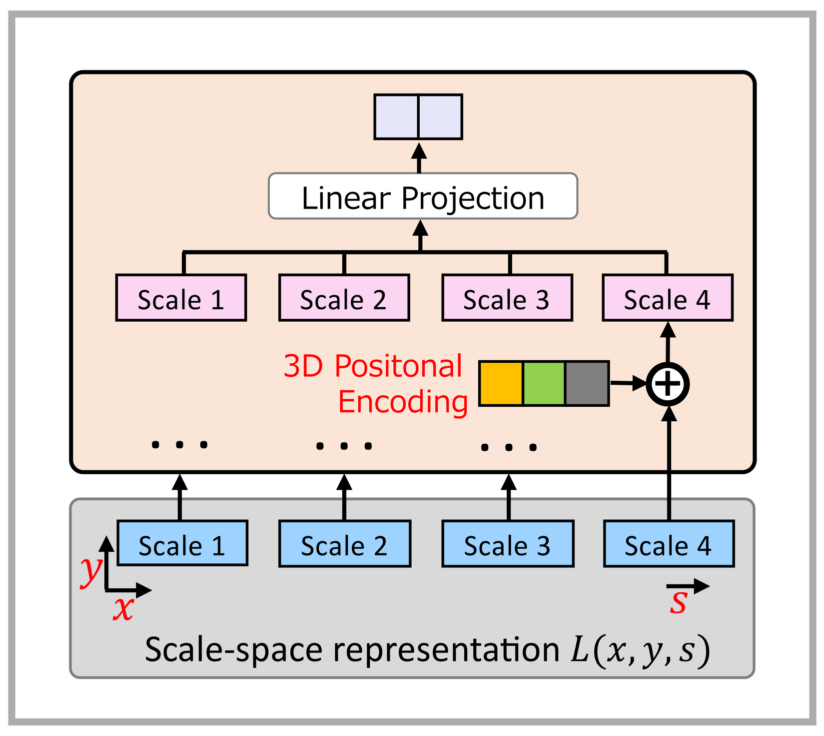
Patching



Patch projection



Scale-space positional Encoding



Experiments

We report the standard accuracy and robustness performance on ImageNet-1k.

Our model: Scale-space-based Robust Vision Transformer (SRVT)
Baseline model: Robust Vision Transformer (RVT) [Mao+ 22]
Evaluation metrics: Top-1 Accuracy (clean, FGSM and PGD), mCE on ImageNet-C
Model sizes: SRVT-Ti (8.6M), SRVT-S (22.1M), SRVT-M (49.1M)
Results: Our model architecture design significantly enhances the robustness against adversarial perturbations and common corruptions.

Model	mCE↓	Gauss.	Shot	Imp.	Defoc.	Glass	Mot.	Zoom	Snow	Frost	Fog	Bright	Cont.	Elas.	Pixel	JPEG
RVT-Ti	58.2	**48.4**	**50.0**	49.3	66.8	78.5	61.8	73.2	53.8	59.2	48.1	48.4	42.3	73.2	**58.5**	58.8
SRVT-Ti	**56.8**	48.5	50.4	**48.7**	**64.4**	**76.3**	**61.1**	**72.0**	**53.6**	**55.7**	**46.9**	**47.2**	**39.6**	**70.5**	59.2	**58.1**
RVT-S	50.1	41.5	43.4	**41.3**	58.4	71.4	**55.2**	67.0	47.2	50.0	38.8	40.8	35.2	64.6	**47.0**	50.2
SRVT-S	**49.3**	**41.3**	**43.2**	41.7	**57.1**	**68.7**	56.0	**66.7**	**45.8**	**45.7**	**37.4**	**39.8**	**33.7**	**63.9**	48.9	**49.9**
SRVT-M	48.4	40.8	42.1	38.9	56.3	67.6	50.7	49.4	44.6	48.0	38.7	40.2	34.2	62.6	47.9	49.7

Corruption error on ImageNet-C

Model	Params (M)	IN-1k Top-1	Robustness Benchmarks FGSM↑	PGD↑	IN-C↓
ResNet50 [19]	25.6	76.1	12.2	0.9	76.7
Inception-v3 [52]	27.2	77.4	22.5	3.1	80.6
RegNetY-4GF [48]	20.6	79.2	15.4	2.4	68.7
EfficientNet-B4 [53]	19.3	83.0	44.6	18.5	71.1
ResNeXt50 [64]	25.0	79.8	34.7	13.5	64.7
DeepAugment [21]	25.6	75.8	27.1	9.5	53.6
ANT [50]	25.6	76.1	17.8	3.1	63.0
AugMix [23]	25.6	77.5	20.2	3.8	65.3
AA CNN [72]	25.6	79.3	32.9	13.5	68.1
Debiased CNN [36]	25.6	76.9	20.4	5.5	67.5
DeiT-S [54]	22.1	79.9	40.7	16.7	54.6
ConViT-S [7]	27.8	81.5	41.0	17.2	49.8
Swin-T [39]	28.3	81.2	33.7	7.3	62.0
PVT-Small [58]	24.5	79.9	26.6	3.1	66.9
PiT-S [25]	23.5	80.9	41.0	16.5	52.5
TNT-S [18]	23.8	81.5	33.2	4.2	53.1
T2T-ViT_t-14 [68]	21.5	81.7	40.9	11.4	53.2
RVT-S [45]	22.1	81.7	51.3	26.2	50.1
SRVT-S (Ours)	22.1	**82.0**	**55.5**	**32.9**	**49.3**

Comparison with SOTA models

Conclusion and Future Work

We introduced a simple yet effective approach, scale-space tokenization, to improve adversarial and out-of-distribution robustness. Future work could explore other factors that enhance the robustness and incorporate them into the scale-space representation.