# **Rethinking the Design Principles of Robust Vision Transformer**

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### **Abstract**

Recent advances on Vision Transformers (ViT) have shown that self-attention-based networks, which take advantage of long-range dependencies modeling ability, surpassed traditional convolution neural networks (CNNs) in most vision tasks. To further expand the applicability for computer vision, many improved variants are proposed to re-design the Transformer architecture by considering the superiority of CNNs, i.e., locality, translation invariance, for better performance. However, these methods only consider the standard accuracy or computation cost of the model. In this paper, we rethink the design principles of ViTs based on the robustness. We found some design components greatly harm the robustness and generalization ability of ViTs while some others are beneficial. By combining the robust design components, we propose Robust Vision Transformer (RVT). RVT is a new vision transformer, which has superior performance and strong robustness. We further propose two new plug-and-play techniques called position-aware attention rescaling and patch-wise augmentation to train our RVT. The experimental results on ImageNet and six robustness benchmarks show the advanced robustness and generalization ability of RVT compared with previous Transformers and state-of-the-art CNNs. Our RVT-S\* also achieves Top-1 rank on multiple robustness leaderboards including ImageNet-C and ImageNet-Sketch. The code will be available at https://github.com/ vtddqqq/Robust-Vision-Transformer.

### 1. Introduction

There have been continuous researches on Transformer models in natural language processing (NLP) applications, e.g., BERT [6] and GPT [25]. Following the popularity of transformers in NLP applications, there has sparked particular interest in investigating whether transformer can be a primary backbone architecture for computer vision applica-

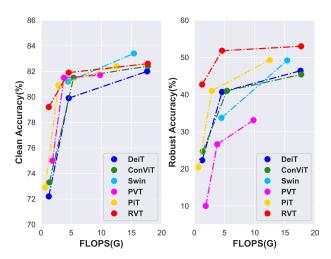


Figure 1. Comparison between RVT and the baseline transformers. The robust accuracy in figure is recorded under FGSM [8] adversary.

tions previously dominated by convolution neural networks (CNNs).

Recently, Vision Transformers (ViT) [7] successfully applies a pure transformer to process non-overlapping image patches for classification and achieves excellent results on multiple image recognition benchmarks. Since then, ViT have inspired several attempts at improving the efficiency from different aspects. For example, DeiT [32] further introduces the teacher-student strategy which enables training of high-performance ViT models with smaller datasets, and T2T-ViT [37] encodes the local structure by introducing a layer-wise Tokens-to-Token (T2T) transformation. Compared to the mainstream residual networks (ResNets) [11], the transformer-based models achieve better performance by taking advantage of self-attention mechanism to learn long-range dependencies between the input tokens.

While there is no doubt that these self-attention-based models are very successful in solving many tasks [23, 12], concerns are naturally raised about the intrinsic influence of network architecture on model robustness and generalization. We give an empirical assessment of existing ViT models in Figure 1. Surprisingly, although all ViT variants

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reproduce the standard accuracy claimed in paper, some of their modification may bring devastating damages on model robustness and generalization. A vivid example is PVT [34], which is well performed on clean test set but suffered with more than 10% drop of robust accuracy compared with original ViT model.

To mitigate this pitfall, we focus on systematically understanding resilience of self-attention-based models to abnormal inputs in this paper, where adversarial examples, common corruption examples and out-of-distribution examples are involved. Specifically, we analyse the effect of different patch embedding, position embedding, transformer blocks and classification head whose impact on the robustness has never been thoroughly studied. By plugging robustness components in the ViTs, we therefore propose a Robust Vision Transformer (RVT) that addresses a new and important goal: achieve the new state-of-the-art on accuracy and robustness compared to other ViT variants. To train RVT, we further propose a soft, sequential, position-aware attention scaling (which we abbreviate as PAAS) method to enhance the robustness of RVT. At the same time, we introduce Patch-wise Augmentation before tokenization used in RVT, which yields better performance on robustness even without extra inference cost. Finally, with RVT, we can build an augmented Robust Vision Transformer\* by combining PASS and patch-wise augmentation training strategy. Our contributions are three-folds:

- Through a series of exploration experiments, some components in ViTs are shown to be harmful for robustness. By adopting these observations, we carefully designing a Robust Vision Transformer (RVT) model, that exhibits new state-of-the-art on accuracy and robustness compared to other ViT variants.
- We introduce a position-aware attention scaling (PAAS) method to improve self-attention mechanism by activating major attention with strong position correlation. Moreover, we propose a simple and general patch-wise augmentation method for patch sequences which adds rich affinity and diversity to training data.
- Experimental results show that RVT achieves superior robustness and generalization performance on ImageNet and six robustness benchmarks, when compared to previous Transformers and state-of-the-art CNNs. An extension from RVT to RVT\*, that achieves Top-1 rank on multiple robustness benchmarks.

### 2. Robustness Analysis of Design Components

We give the robustness analysis of four main design components in ViTs: patch embedding, position embedding, transformer blocks and classification head. Deit-Ti [32] is used as the base model. If no special remarks, robust accuracy stands for the test accuracy under FGSM [8] adversary.

### 2.1. Patch Embedding

Low-level feature of patches. ViTs tokenize an image by spliting it to patches with size of  $16 \times 16$  or  $32 \times 32$ . Such a simple tokenization makes the models hard to capture low-level structures such as edges and corners. To extract low-level feature of patches, CeiT [36], LeViT [9] and TNT [10] use a convolutional stem instead of the original linear layer, T2T-ViT [37] leverages self-attention to model dependencies among neighboring pixels. However, these methods merely focus on the test accuracy. To answer how is the robustness affected by leveraging low-level feature of patches, we evaluate two types of patch embedder: convolutional embedder and tokens-to-tokens embedder, proposed by CeiT and T2T-ViT respectively. As shown in Table 3, patch embedding which encodes low-level features have stronger classification ability. It also has a positive effect on the model robustness as more detailed visual features are exploited. Tokens-to-tokens embedder is superior than convolutional embedder on accuracy and robustness, but it has quadratic complexity with the expansion of image size, requiring more computation costs.

### 2.2. Position Embedding

The way of position encoding. We study the robustness of ViTs when different ways of positional encoding are used. We first explore the necessity of position embeddings. ViT trained without position embeddings has 4% drop of accuracy, and this performance gap even can be larger on robustness. We found with no position encoding mechanism, ViT fails to discriminate based on the shape of object, which leads to 8% accuracy drop on ImageNet-Sketch datasets. Therefore, position embedding is indispensable in ViTs. Concerning the ways of positional encoding, learned absolute, sin-cos absolute, learned relative [29] and inputconditioned [1] position representations are compared. In Table 1, the result suggests that most position encoding methods have no big impact on the robustness, and some of them even have a negative effect. Especially, CPE [1] encodes position embeddings conditioned on the inputs, which leads the position information to be changed easily by the input perturbations. This is obviously unreasonable and makes the model more vulnerable under attacks. Such a fragility of position embeddings also motivates us to design a more robust position encoding method.

	positional embedding	Acc	Robust Acc
(i)	none	68.3	15.8
(ii)	learned absolute position	72.2	22.3
(iii)	sin-cos absolute position	72.0	21.9
(iv)	learned relative position [29]	71.8	22.3
(v)	input-conditioned position [1]	72.4	21.5

Table 1. **Effect of different positional embeddings.** We use Deit-Ti as the base model.

variant	$[S_1, S_2, S_3, S_4]$	FLOPs	Mem	Acc	Robust Acc
V1	[0, 0, 12, 0]	1.3	1.1	72.2	22.3
<u>V2</u>	[0, 0, 10, 2]	1.2	1.1	74.8	24.3
V3	[0, 2, 10, 0]	1.5	1.7	73.8	22.0
V4	[0, 2, 8, 2]	1.4	1.7	76.4	22.3
V5	[2, 2, 8, 0]	3.4	6.0	73.4	17.0
V6	[2, 2, 6, 2]	3.4	6.0	76.4	17.5

Table 2. **Effect of stage distribution.** We ablate the number of blocks in stages  $S_1$ ,  $S_2$ ,  $S_3$ ,  $S_4$  of **DeiT-Ti**, where  $S_1$  is the stage with the largest  $56 \times 56$  input spatial dimension, and gradually reduced to half of the original in later stages. The GPU memory consumption is tested on input with batch size of 64.

**Block-wise position encoding.** Generally positional embeddings are included only on input to the sequence of attention blocks. However, as proposed in [9], lower blocks and higher blocks may need different positional information, and providing positional representations within each attention block benefits the performance. This conclusion is the same as the result in Table 6. Similarly, the result shows the block-wise position embeddings are also beneficial to the robustness.

#### 2.3. Transformer Blocks

**Stage distribution.** Mordern CNNs always start with a feature of large spatial sizes and a small channel size and gradually increase the channel size while decreasing the spatial size. The different sizes of feature maps constitute the multi-stage convolution blocks. Shown by previous works [2], such a design contributes to the expressiveness and generalization performance of the network. PVT [34], PiT [17] and Swin [21] employ this principle into ViTs to change the spatial dimensions. To measure the robustness variance with changing of stage distribution, we slightly modify the Deit-Ti architecture to get six variants in Table 2. We keep the overall number of transformer blocks consistent to 12 and replace some of them with smaller or larger spatial dimensions. By comparing these variants, we found both cases of spatial pooling improve the classification accuracy, benefit from the extraction of hierarchical image features. In terms of robustness, transformer blocks with different spatial sizes show different effects. An experimental conclusion is that the model will get worse on robustness when it contains more transformer blocks with large input spatial dimensions. On the contrary, reducing the input spatial dimensions gradually at later transformer blocks contributes to modest enhancement of robustness. Besides, we also observe that having more blocks with larger input spatial size will increase the amount of FLOPs and memory consumption. To achieve the best trade-off, we think V2 is the most compromising choice in this paper.

**Number of Head.** Another design component is changing the number of heads. ConViT [4] and LeViT [9] both

Method	Patch Emb. Conv.   T2T		Locality SA FFN		CLS	Acc	Rob. Acc
Deit-Ti					/	72.2	22.3
a	1				1	73.6	23.2
b		1			1	74.9	25.4
c			1		1	69.1	21.0
d				1	1	73.9	31.9
e						72.4	28.4

Table 3. Ablations on patch embeddings, network locality and CLS toekn. ✓indicates the use of the corresponding component.

Heads	1	2	4	6	8	12
Acc	69.0	71.7	73.1	73.4	73.9	73.5
Rob. Acc	17.6	21.4	22.8	24.6	25.2	24.7

Table 4. The performance variance with the number of heads. **DeiT-Ti** with head number of 1, 2, 4, 6, 8 and 12 are trained for comparison.

use more self-attention heads and smaller dimensions of keys and queries to achieve better performance at a controllable FLOPs. To study how does the number of heads affect the robustness, we train Deit-Tiny with different head numbers. Once the number of heads increases, we meanwhile reduce the head dimensions to ensure the overall feature dimensions are unchanged. The results are shown in Table 4. In generally understanding in NLP [24], larger number of heads will increase the redundancy and some of them can even be removed without significantly impacting performance. However, we found ViTs in computer vision are totally different and shows great starvation for attention head. As shown in the table, the accuracy and robustness still gain great improvement with the head increasing till to 8. We think that more attention heads supply various aspects of attentive information on the input. Such complete and non-redundant attentive information also introduces more visual relations which are prone to be neglect by model with less heads, thus increases the robustness.

Locality in Self-Attention. Vanilla self-attention calculates the pair-wise attention of all sequence elements. But for image classification, local regions need to be paid more attention than remoter regions. Swin [21] limits the self-attention computation to non-overlapping local windows on the input. This hard coded locality of self-attention enjoys great computational efficiency and has linear complexity with respect to image size. Although local window self-attention can also get competitive accuracy, in this work we found it is harmful to the model robustness. The result in Table 3 shows after modifying self-attention to the local version, both standard and robust accuracy are getting worse. We think this phenomenon may be partly caused by the destruction of long-range dependencies modeling in ViTs.

**Locality in FFN.** LocalViT [20] and CeiT [36] introduce locality mechanism into ViTs by adding a depth-wise con-

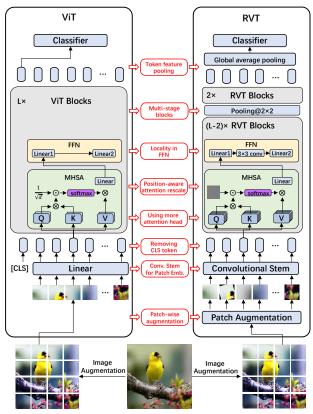


Figure 2. Overall architecture of the proposed Robust Vision Transformer (RVT).

volution in feed-forward networks (FFN). Our experiment in Table 3 verifies that locality in FFN greatly improves both accuracy and robustness. We think the reason lies in two aspect. First, compared with self-attention locality, FFN locality will not damage the long-term dependencies modeling ability of ViTs. The merit of ViTs can be inherited. Second, original FFN only encodes token representation based on itself, while local-aware FFN encodes both the current and its neighbors as token representation. Such a local information aggregation makes ViTs more rubust to the input disturbance.

#### 2.4. Classification Head

Classification token. CNNs adopt a global average pooling layer before the classifier to integrate visual features at different spatial locations. This practice also inherently takes advantage of the translation invariance of the image. However, ViTs use an additional classification token (CLS) to perform classification, are not translation-invariant. To get over this shortcoming, CPVT [1] and LeViT [9] remove the CLS token and replace it by average pooling along last layer sequential output of the Transformer. We compare models trained with and without CLS token. The result shows the adversarial robustness can be slightly improved by removing CLS token. And models which only rely on

CLS token for classification, are more vulnerable to adversarial attacks. Also we found removing CLS token have little help for accuracy, which can be beneficial from the desired translation-invariance.

**Feature normalization.** A main difference of CNNs and ViTs in classification head is whether to normalize the feature before feeding it to the last linear classification layer. ViTs conduct an extra layer normalization for classified feature while CNNs do not. To study the role of feature normalization, we trained Deit-Tiny with and without last layer normalization respectively. The test accuracy and robust accuracy are dropped slightly after removing the layer normalization, which demonstrates that feature normalization is necessary for ViTs and it also helps to the model robustness to some extent.

### 2.5. Combination of Robust Components

In the above, we separately analyse the effect of each design component in the ViTs. To make use of these findings, we combine the selected useful components, listed in follows:

#### Takeaways:

- (i) Extract low-level feature of patches using a convolutional stem;
- (ii) Adopt the multi-stage design of ViTs, where the spatial dimension is reduced in later transformer blocks;
- (iii) Use more self-attention heads with reduced dimension;
- (iv) Introduce locality in FFN with  $3\times3$  depth-wise convolutions;
- (v) Replace CLS token with token feature pooling and normalizing.

As we found the effects of the above modifications are superimposed, we adopt all of these design components into ViTs, the resultant model is called Robust Vision Transformer (RVT). RVT has achieve the new state-of-the-art on accuracy and robustness compared to other ViT variants. To further improve the performance, in this paper, we propose two novel techniques to training our RVT. First is the position-aware attention scaling, which will be introduced in section 3. The second is the training time augmentation called patch-wise data augmentation. Both of them are also applicable to other ViT models.

# 3. Position-Aware Attention Scaling

In this section, we introduce our proposed position encoding mechanism called Position-Aware Attention Scaling (PAAS), which modifies the rescaling operation in the dot product attention to a more generalized version. To start with, we introduce the scaled dot-product attention in transformer firstly. And then the modification of PAAS will be explained.

**Scaled dot-product attention** Scaled dot-product attention is a key component in Multi-Head Self Attention layer (MHSA) of transformer. MHSA first generates set of query

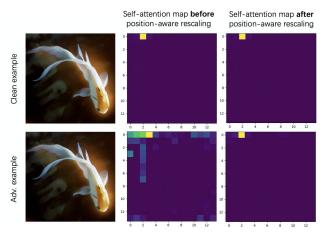


Figure 3. Visualization of self-attention before and after the position-aware attention scaling.

 $Q \in \mathbb{R}^{N \times d}$ , key  $K \in \mathbb{R}^{N \times d}$ , value  $V \in \mathbb{R}^{N \times d}$  with the corresponding projection. Then the *query* vector  $q \in \mathbb{R}^d$  is matched against the each key vector in K. The output is the weighted sum of a set of N value vectors v based on the matching score. This process is called scaled dot-product attention:

$$\operatorname{Attention}(Q, K, V) = \operatorname{SoftMax}(QK^T/\sqrt{d})V \qquad (1)$$

For preventing extremly small gradients and stabilizing the training process, each element in  $QK^T$  multiplies by a constant  $\frac{1}{\sqrt{d}}$  to be rescaled into a standard range.

**Position-aware attention scaling** The above attention scaling method is position-unaware, that is to say, every dot-product of q-k pairs are treated equally with a constant rescale factor. We think such a design is low efficiency and has no contribution for the model capacity. In this work, a more efficient position-aware attention scaling method is proposed. To make attention scaling positionaware, we first define a learnable position importance matrix  $W_p \in \mathbb{R}^{N \times N}$ , which presents the importance of each pair of q-k. The oringinal scaled dot-product attention is modified as follows:

Attention
$$(Q, K, V) = \text{SoftMax}(QK^T \odot (W_p/\sqrt{d}))V,$$
(2)

where  $\odot$  is the element-wise product. As  $W_p$  is input independent and only determined by the position of each q, k in the sequence, our position-aware attention scaling can also serve as a position representation, instead of traditional position embedding. The overall self-attention can be decoupled into two parts: the  $QK^T$  term presents the content-based attention, and  $W_p/\sqrt{d}$  term acts as the position-based attention. This untied design offers more expressiveness by removing the mixed and noisy correlations [18].

**Robustness of PAAS** As mentioned in section 2.2, most traditional position encoding methods have no contribution to the model robustness, and some of them even do a negative effect. Differently, our proposed PAAS can improve the model robustness effectively. This superior property relies on the position importance matrix  $W_p$ , which acts as a soft attention mask on each position pair of q-k. Figure 3 shows a case how PAAS fixes the unexpected input errors. The first column is the input example and next two columns are self-attention maps before and after PAAS respectively. Without PAAS, an adversarial input can make many unrelated regions activated and produce a noisy self-attention map, which leads the model mis-classified. To filter out these noises, PAAS suppresses the redundant positions irrelevant for classification in self-attention map, by a learned small multiplier in  $W_p$ . Finally only the regions important for classification are activated. We experimentally validate that PAAS can provide certain defense power against some white-box adversaries, e.g., FGSM [8], PGD [22]. Not limited to adversarial attack, it also helps to the corruption and out-of-distribution generalization. Details can be referred to section 5.3.

# 4. Patch-Wise Augmentation

Image augmentation is a strategy that prevents the overfitting by increasing the diversity of data available for training models, using some common image transformations such as cropping, padding, horizontal flipping as so on. This strategy is especially important for ViTs since a biggest shortcoming of ViTs is the worse generalization ability when trained on relatively small-size datasets, while this shortcoming can be remedied by sufficient data augmentation [32]. On the other hand, a rich data augmentation also helps with robustness and generalization, which has been verified in previous works [15].

For improving the diversity of the augmented training data, we propose the patch-wise data augmentation strategy for ViTs, which imposes diverse augmentation on each input image patches at training time. Our motivation comes from the special image encoding scheme of ViTs. Compared with CNNs, ViTs not only extract intra-patch features but also concern the inter-patch relations. We think the traditional augmentation which randomly transforms the whole image could provide enough intra-patch augmentation. However, it lacks the diversity on inter-patch augmentation, as all of patches have the same transformation at one time. To impose more inter-patch diversity, we retain the original image-level augmentation, and then add an following patch-level augmentation on each image patches. For simplicity, only three basic image transformations are considered for patch-level augmentation: random resized crop, random horizontal flip and random gaussian noise

Robustness of Patch-Wise Augmentation Same with the augmentations like MixUp [38], AugMix [15], RandAugment [3], Patch-Wise Augmentation also benefit the model robustness. It effects on the phases after conventional image-level augmentations, and provides the meaningful perturbations on patch sequence input. This improved input diversity can further reduce the risk of over-fitting, and enhance the model generalization under unexpected inputs.

# **5. Experiments**

### 5.1. Experimental Settings

**Implementation Details** All of our experiments are performed on the NVIDIA 2080Ti GPUs. For RVT, we adopt the best settings investigated in section 2. For RVT\*, we add PAAS on first 10 transformer blocks, and remove the original position embedding. The patch-wise augmentation uses the combination of *random resized crop*, *random horizontal flip* and *random gaussian noise*, whose hyperparameters is showed in section 5.4. For other training hyperparameters, we keep the same with DeiT [32].

**Evaluation Benchmarks** We adopt the ImageNet-1K [5] dataset for standard performance evaluation. It consists of 1.2M training images belonging to 1000 classes, and 50K validation images. Except for this, no other largescale dataset is needed for pre-training. For robustness evaluation, we test our RVT in three aspect: 1) for adversarial robustness, we adopt white-box attack algorithms FGSM [8] and PGD [22] to generate adversarial examples on ImageNet-1K validation set, and feed into RVT to get the accuracy. ImageNet-A [16] is used for evaluating the model under natural adversarial example. 2) for common corruption robustness, we calculate the mean corruption error (mCE) on ImageNet-C [14] dataset. mCE is the mean error rate normalized based AlexNet's errors, and the smaller mCE means the more robust of the model. 3) for out-of-distribution robustness, we adopt ImageNet-R [13] and ImageNet-Sketch [33] datasets. The former contains 30,000 image renditions for 200 ImageNet classes, e.g., art, cartoons, deviantart, etc. The latter has 50 sketch images for each of the 1000 ImageNet classes, resulting in 50000 sketch images, which can evaluate the recognition power of the model when texture or color information is missing.

#### 5.2. Standard Performance Evaluation

For standard performance evaluation, we compare our method with state-of-the-art classification methods including Transformer-based models and representative CNN-based models in Table 5.

Compared to CNNs-based models, RVT has surpassed most of CNN architectures with fewer parameters and FLOPs. RVT-Ti\* achieves 79.2% Top-1 accuracy on

ImageNet-1K validation set, which is competitive with currently popular ResNet [11] and RegNet [26] series, but only has 1.3G FLOPs and 10.9M parameters (around 60% lower than CNNs). With the same computation cost, RVT-S\* obtains 81.9% test accuracy, 2.9% higher than ResNet-50. This result is closed to EfficientNet-B4 [31], however EfficientNet-B4 requires larger 380×380 input size and has much lower throughput.

Compared to Transformer-based models, our RVT also surpasses the previous vision transformers with a large margin. We find just combining the robust design components can make RVT-Ti get 78.4% Top-1 accuracy, which has been a state-of-the-art on tiny version of vision transformers. By adopting our newly proposed position-aware attention scaling and patch-wise data augmentation, RVT-Ti\* can further improve 0.8% on RVT-Ti with little additional computation cost. For other scales of the model, RVT-S\* and RVT-B\* also achieve a good promotion. Although the improvement becomes smaller with the increase of model capacity, we think the advance of our model is still obvious as it strengthen the model ability in various views such as robustness and out-of-domain generalization.

#### 5.3. Robustness Evaluation

We employ a series of benchmarks to evaluate the model robustness on different aspects. Among them, ImageNet-C (IN-C) uses mCE to assess the robustness under corruptions. All other benchmarks use Top-1 accuracy on test data if no special illustration. The results are reported in Table 5.

Adversarial Robustness. For evaluate the adversarial robustness, we adopt single-step attack algorithm FGSM [8] and multi-step attack algorithm PGD [22] with steps t=5, step size  $\alpha = 0.5$ . Both attackers perturb the input image with max magnitude  $\epsilon = 1$ . Table 5 suggests that the adversarial robustness has a strong correlation with the design of model architecture. With similar model scale and FLOPs, most Transformer-based models have higher robust accuracy than CNNs under adversarial attacks. This phenomenon may attribute to the special design of ViTs. Some modifications on ViTs or CNNs will also weaken or strengthen the adversarial robustness. For example, Swin-T [21] introduce window self-attention for reducing the computation cost but damaging the adversarial robustness, and EfficientNet-B4 use smooth activation functions which is helpful with adversarial robustness.

We summarize the robust design experiences of ViTs in this work. The resultant RVT model achieves superior performance on both FGSM and PGD attackers. In detail, RVT-Ti and RVT-S get 10% improvement on FGSM, compared with the previous ViT variants. This advance is further expanded by our PAAS and patch-wise augmentation. Adversarial robustness seems unrelated with standard per-

Table 5. The performance of RVT and several SOTA CNNs and Transformers on ImageNet and six robustness benchmarks. For clear comparison, we put the models with similar FLOPs together. RVT\* represents the RVT model introduced in section 2.5 but trained with our proposed PAAS and patch-wise augmentation. Except for different architectures, we also compare some SOTA methods, e.g., ANT, DeepAugment, AugMix, which aims at improving the model robustness based on ResNet-50.

-	FLOPs Params				ImageNet Robus				ıstness Benchmarks			
Group Model		(G)	(M)	Top-1	Top-5	FGSM	PGD	IN-C (↓)	IN-A	IN-R	IN-SK	
	ResNet-50 [11]	4.1	25.6	76.1	86.0	12.2	0.9	76.7	0.0	3.4	24.1	
	ResNet-50* [11]	4.1	25.6	79.0	94.4	36.3	12.5	65.5	5.9	3.8	31.5	
	Inception v3 [30]	5.7	27.2	77.4	93.4	22.5	3.1	80.6	10.0	3.5	27.6	
	RegNetY-4GF [26]	4.0	20.6	79.2	94.7	15.4	2.4	68.7	8.9	3.5	25.9	
	EfficientNet-B4 [31]	4.4	19.3	83.0	96.3	44.6	18.5	71.1	26.3	4.2	34.1	
CNNs	ResNeXt50-32x4d [35]	4.3	25.0	79.8	94.6	34.7	13.5	64.7	10.7	3.7	29.3	
	DeepAugment [13]	4.1	25.6	75.8	92.7	27.1	9.5	53.6	3.9	4.2	32.6	
	ANT [28]	4.1	25.6	76.1	93.0	17.8	3.1	63.0	1.1	3.5	26.3	
	AugMix [15]	4.1	25.6	77.5	93.7	20.2	3.8	65.3	3.8	3.7	28.5	
	Anti-Aliased CNN [39]	4.2	25.6	79.3	94.6	32.9	13.5	68.1	8.2	3.6	29.6	
	Debiased CNN [19]	4.1	25.6	76.9	93.4	20.4	5.5	67.5	3.5	3.7	28.4	
	DeiT-Ti [32]	1.3	5.7	72.2	91.1	22.3	6.2	71.1	7.3	3.3	20.2	
	ConViT-Ti [4]	1.4	5.7	73.3	91.8	24.7	7.5	68.4	8.9	3.4	22.4	
	PiT-Ti [17]	0.7	4.9	72.9	91.3	20.4	5.1	69.1	6.2	3.4	21.6	
	PVT-Tiny [34]	1.9	13.2	75.0	92.5	10.0	0.5	79.6	7.9	3.1	21.5	
	RVT-Ti	1.3	8.6	78.4	94.2	34.8	11.7	58.2	13.3	3.9	30.0	
	RVT-Ti*	1.3	10.9	79.2	94.7	42.7	18.9	57.0	14.4	3.9	30.4	
	DeiT-S [32]	4.6	22.1	79.9	95.0	40.7	16.7	54.6	18.9	3.7	29.4	
	ConViT-S [4]	5.4	27.8	81.5	95.8	41.0	17.2	49.8	24.5	3.9	33.1	
	Swin-T [21]	4.5	28.3	81.2	95.5	33.7	7.3	62.0	21.6	3.7	29.1	
	PVT-Small [34]	3.8	24.5	79.9	95.0	26.6	3.1	66.9	18.0	3.5	27.2	
	PiT-S [17]	2.9	23.5	80.9	95.3	41.0	16.5	52.5	21.7	3.8	30.8	
Transformers	TNT-S [10]	5.2	23.8	81.5	95.7	33.2	4.2	53.1	24.7	3.9	31.6	
	T2T-ViT_t-14 [37]	6.1	21.5	81.7	95.9	40.9	11.4	53.2	23.9	4.0	32.5	
	RVT-S	4.7	22.1	81.7	95.7	51.3	26.2	50.1	24.1	4.1	35.0	
	RVT-S*	4.7	23.3	81.9	95.8	51.8	28.2	49.4	25.7	4.2	34.7	
	DeiT-B [32]	17.6	86.6	82.0	95.7	46.4	21.3	48.5	27.4	3.8	32.4	
	ConViT-B [4]	17.7	86.5	82.4	96.0	45.4	20.8	46.9	29.0	4.2	35.7	
	Swin-B [21]	15.4	87.8	83.4	96.4	49.2	21.3	54.4	35.8	4.2	32.4	
	PVT-Large [34]	9.8	61.4	81.7	95.9	33.1	7.3	59.8	26.6	3.7	30.2	
	PiT-B [17]	12.5	73.8	82.4	95.7	49.3	23.7	48.2	33.9	3.9	32.3	
	T2T-ViT_t-24 [37]	15.0	64.1	82.6	96.1	46.7	17.5	48.0	28.9	4.2	35.4	
	RVT-B	17.7	86.2	82.5	96.0	52.3	27.4	47.3	27.7	4.2	35.8	
	RVT-B*	17.7	91.8	82.6	96.0	53.0	29.9	46.8	28.5	4.3	36.0	

formance. Although models like Swin-T, TNT-S get higher standard accuracy than DeiT-S, their adversarially robust accuracy is well below the baseline. However, our RVT model can achieve the best trade-off between standard performance and adversarial robustness.

Common Corruption Robustness. To metric the model degradation on common image corruptions, we present the mCE on ImageNet-C in Table 5. We also list some methods contained on ImageNet-C Leaderboard<sup>1</sup>, which are bulit based on ResNet-50. Our RVT-S\* gets 49.4 mCE, which has 4.2 improvement on top-1 method DeepAugment [13] in the leaderboard, and bulids the new state-of-the-art. Although RVT-S\* is based on Transformer, we think it is comparable with ResNet-50 as they have similar FLOPs and parameter number. It also indicates that Transformer-based

models have a natural advantage in dealing with image corruptions. Because ViTs are good at long-range dependencies modeling, which makes it easier to learn the shape feature than CNNs. Such a shape feature is more robust and less likely to be destroyed by image corruptions.

Out-of-distribution Robustness. We test the model generalization on out-of-distribution data by reporting the accuracy on ImageNet-R and ImageNet-Sketch in Table 5. The performance gap is not obvious on ImageNet-R, as the task is hard for most compared models. Even though, our RVT also wins other ViT models on out-of-distribution generalization. ImageNet-Sketch can be seen as a sub-task of domain generalization, where input images miss the texture and color information for classification. As the superiority of Transformer-based models on capturing shape feature mentioned above, our RVT-S also surpasses most CNN and ViT models and get 35.0% test accuracy, which is located

https://github.com/hendrycks/robustness

at top-1 rank on ImageNet-Sketch Leaderboard<sup>2</sup>.

#### **5.4. Ablation Studies**

we conduct ablation studies on the proposed components of PAAS and patch-wise augmentation in this section. Other modifications of RVT are not involved since they have been analyzed in section 2. All of our ablation experiments are based on the RVT-Ti model on ImageNet.

Single layer PAAS vs. Multiple layer PAAS We evaluate whether using PAAS on multiple transformer blocks can benefits the performance or robustness. The result is suggested in Table 6. The way of position embedding in original ViT model is adopted for comparison. Applying PAAS only on first block yields smallest improvement. With more transformer blocks using PAAS, the standard and robust accuracy gain greater enhancement. After applying PAAS on 5 blocks, the benefit of PAAS gets saturated. There will be the same trend if we replace PAAS with the original position embedding. But the original position embedding is not performed as good as our PAAS on both standard and robust accuracy.

Different types of basic augmentation. Due to the limited training resources, we only test three basic image augmentations: random resized crop, random horizontal flip and random gaussian noise. For random resized crop, we crop the patch according to the scale sampled from [0.85, 1.0], then resize it to original size with aspect ratio unchanged. We set the mean and standard deviation as 0 and 0.01 for random gaussian noise. For each transformation, we set the applying probability p = 0.1. Other hyper-parameters are consistent with the implementation in Kornia [27]. As shown in Table 7, we can see both three augmentations are beneficial of performance and robustness. Among them, random gaussian noise is the better choice as it helps for more robustness improvement.

Layers	Pos. Emb.	Acc	Rob. Acc	Aug RC	mentat GN	ions HF	Acc	Rob. Acc
0-1	Ori.	78.2	34.1	/			78.9	41.5
0-1	Ours	78.4	34.3		1		79.0	42.0
0-5	Ori.	78.4	34.6			1	79.1	41.3
	Ours	78.6	35.2	✓		1	78.8	41.3
0-10	Ori.	78.4	34.8		✓	1	79.0	41.9
	<u>Ours</u>	78.6	35.3	✓	✓	/	79.2	41.7

Table 6. Comparison of sin-Table 7. Ablation experiments on gle and multiple block PAAS. patch-wise augmentation. RC, GN, Ori. stands for the learned ab- HF represent *random resized crop*, solute position embedding in *random gaussian noise* and *random* original ViTs.

horizontal flip respectively.

Combination of basic augmentations. We further evaluate the combination of basic patch-wise augmentations. For traditional image augmentation, combining multiple basic transformation can improve the diversity of augmented images, and thus benefit the model training. As shown in Table 7, the benefit is marginal for combining basic patch-wise augmentations, but combination of three is still better than using only single augmentation. In this paper, we adopt the combination of all basic augmentations. If the training cost is limited, using only single augmentation such as *random gaussian noise* can also be considered.

Effect on other ViT architectures. For showing the effectiveness of our proposed position-aware attention scaling and patch-wise augmentation, we apply them to train other ViT models. Deit-Ti, ConViT-Ti and PiT-Ti are adopted as the base model. The experimental results are shown in Table 8, with combining the proposed techniques into these base models, all the tested model achieve significant improvement. In Table 8, all the improved models get more than 1% and 5% promotion on standard and robust accuracy on average.

•	Vanilla models	Acc	Acc Rob. Acc Improved models		Acc	Rob. Acc
	DeiT-Ti	72.2	22.3	DeiT-Ti*	74.4	29.9
	ConViT-Ti	73.3	24.7	ConViT-Ti*	74.4	30.7
	PiT-Ti	72.9	20.4	PiT-Ti*	74.3	27.7

Table 8. Effect of our proposed PAAS and patch-wise augmentation on other ViT architectures.

### 6. Conclusion

Through the exploration experiments, we have investigated the best structure of our Robust Vision Transformer (RVT) by aggregating robust components from ViTs and CNNs. Then we present position-aware attention scaling (PAAS) method to enhance the intrinsic robustness of the self-attention-based RVT. Besides, we have devised a novel patch-wise augmentation that focus on finer feature by operating on sequence of patches. Compared to the ViT counterparts and well-designed CNNs, our RVT achieves outstanding performance consistently on ImageNet and six robustness benchmarks. In addition, extensive experiments validate the significance of our augmented RVT\*, show the effectiveness of our methods.

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