Are Transformers More Robust Than CNNs?

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Abstract

Transformer emerges as a powerful tool for visual recognition. In addition to demonstrating competitive performance on a broad range of visual benchmarks, recent works also argue that Transformers are much more robust than Convolutions Neural Networks (CNNs). Nonetheless, surprisingly, we find these conclusions are drawn from unfair experimental settings, where Transformers and CNNs are compared at different scales and are applied with distinct training frameworks. In this paper, we aim to provide the first **fair & in-depth** comparisons between Transformers and CNNs, focusing on robustness evaluations.

With our unified training setup, we first challenge the previous belief that Transformers outshine CNNs when measuring *adversarial robustness*. More surprisingly, we find CNNs can easily be as robust as Transformers on defending against adversarial attacks, if they properly adopt Transformers' training recipes. While regarding *generalization on out-of-distribution samples*, we show pre-training on (external) large-scale datasets is not a fundamental request for enabling Transformers to achieve better performance than CNNs. Moreover, our ablations suggest such stronger generalization is largely benefited by the Transformer's self-attention-like architectures per se, rather than by other training setups. We hope this work can help the community better understand and benchmark the robustness of Transformers and CNNs. The code and models are publicly available at `https://github.com/ytongbai/ViTs-vs-CNNs`.

1 Introduction

Convolutional Neural Networks (CNNs) have been the widely-used architecture for visual recognition in recent years [21, 36, 38, 15, 20]. It is commonly believed the key to such success is the usage of the convolutional operation, as it introduces several useful inductive biases (*e.g.*, translation equivalence) to models for benefiting object recognition. Interestingly, recent works alternatively suggest that it is also possible to build successful recognition models without convolutions [31, 56, 2]. The most representative work in this direction is Vision Transformer (ViT) [11], which applies the pure self-attention-based architecture to sequences of images patches and attains competitive performance on the challenging ImageNet classification task [32] compared to CNNs. Later works [25, 45] further expand Transformers with compelling performance on other visual benchmarks, including COCO detection and instance segmentation [22], ADE20K semantic segmentation [57].

The dominion of CNNs on visual recognition is further challenged by the recent findings that Transformers appear to be *much more robust* than CNNs. For example, Shao *et al*. [35] observe that the usage of convolutions may introduce a negative effect on models' adversarial robustness, while migrating to Transformer-like architectures (*e.g.*, the Conv-Transformer hybrid model or the pure Transformer) can help secure models' adversarial robustness. Similarly, Bhojanapalli *et al*. [3] report that, if pre-trained on sufficiently large datasets, Transformers exhibit considerably stronger robustness than CNNs on a spectrum of out-of-distribution tests (*e.g.*, common image corruptions [16], texture-shape cue conflicting stimuli [12]).

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Though both [3] and [35] claim that Transformers are preferable to CNNs in terms of robustness, we find that such conclusion cannot be strongly drawn based on their existing experiments. Firstly, Transformers and CNNs are not compared at the same model scale, *e.g.*, a small CNN, ResNet-50 (∼25 million parameters), by default is compared to a much larger Transformer, ViT-B (∼86 million parameters), for these robustness evaluations. Secondly, the training frameworks applied to Transformers and CNNs are distinct from each other (*e.g.*, training datasets, number of epochs, and augmentation strategies are all different), while little efforts are devoted on ablating the corresponding effects. In a nutshell, due to these inconsistent and unfair experiment settings, *it remains an open question whether Transformers are truly more robust than CNNs*.

To answer it, in this paper, we aim to provide the first benchmark to fairly compare Transformers to CNNs in robustness evaluations. We particularly focus on the comparisons between Small Data-efficient image Transformer (DeiT-S) [41] and ResNet-50 [15], as they have similar model capacity (*i.e.*, ∼22 million parameters *vs*. ∼25 million parameters) and achieve similar performance on ImageNet (*i.e.*, 76.8% top-1 accuracy *vs*. 76.3% top-1 accuracy[1]). Our evaluation suite accesses model robustness in two ways: 1) adversarial robustness, where the attackers can actively and aggressively manipulate inputs to approximate the worst-case scenario; 2) generalization on out-of-distribution samples, including common image corruptions (ImageNet-C [16]), texture-shape cue conflicting stimuli (Stylized-ImageNet [12]) and natural adversarial examples (ImageNet-A [17]).

With this unified training setup, we present a completely different picture from previous ones [35, 3]. Regarding adversarial robustness, we find that Transformers actually are no more robust than CNNs—if CNNs are allowed to properly adopt Transformers' training recipes, these two types of models will attain similar robustness on defending against both perturbation-based adversarial attacks and patch-based adversarial attacks. While for generalization on out-of-distribution samples, we find Transformers can still substantially outperform CNNs even without the needs of pre-training on sufficiently large (external) datasets. Additionally, our ablations show that adopting Transformer's self-attention-like architecture is the key for achieving strong robustness on these out-of-distribution samples, while tuning other training setups will only yield subtle effects here. We hope this work can serve as a useful benchmark for future explorations on robustness, using different network architectures, like CNNs, Transformers, and beyond [40, 23].

2 Related Works

Vision Transformer. Transformers, invented by Vaswani *et al*. in 2017 [44], have largely advanced the field of natural language processing (NLP). With the introduction of self-attention module, Transformer can effectively capture the non-local relationships between all input sequence elements, achieving the state-of-the-art performance on numerous NLP tasks [51, 9, 4, 10, 28, 29].

The success of Transformer on NLP also starts to get witnessed in computer vision. The pioneering work, ViT [11], demonstrates that the pure Transformer architectures are able to achieve exciting results on several visual benchmarks, especially when extremely large datasets (*e.g.*, JFT-300M [37]) are available for pre-training. This work is then subsequently improved by carefully curating the training pipeline and the distillation strategy to Transformers [41], enhancing the Transformers' tokenization module [52], building multi-resolution feature maps on Transformers [25, 45], designing parameter-efficient Transformers for scaling [54, 43, 49], *etc*. In this work, rather than focusing on furthering Transformers on standard visual benchmarks, we aim to provide a fair and comprehensive study of their performance when testing out of the box.

Robustness evaluations. Conventional learning paradigm assumes training data and testing data are drawn from the same distribution. This assumption generally does not hold, especially in the real-world case where the underlying distribution is too complicated to be covered in a (limited-sized) dataset. To properly access model performance in the wild, a set of robustness generalization benchmarks have been built, *e.g.*, ImageNet-C [16], Stylized-ImageNet [12], ImageNet-A [17], *etc*. Another standard surrogate for testing model robustness is via adversarial attacks, where the attackers deliberately add small perturbations or patches to input images, for approximating the worst-case evaluation scenario [39, 13]. In this work, both robustness generalization and adversarial robustness are considered in our robustness evaluation suite.

[1]Here we apply the general setup in [42] for the ImageNet training. We follow the popular ResNet's standard to train both models for 100 epochs. Please refer to Section 3 for more training details.

Concurrent to ours, both Bhojanapalli *et al*. [3] and Shao *et al*. [35] conduct the robustness comparisons between Transformers and CNNs. Nonetheless, we find their experimental settings are unfair, *e.g*., models are compared at different capacity [3, 35] or are trained under distinct frameworks [35]. In this work, our comparison carefully align the model capacity and the training setups, which draws completely different conclusions from the previous ones.

3 Settings

3.1 Training CNNs and Transformers

Convolutional Neural Networks. ResNet [15] is a milestone architecture in the history of CNN. We choose its most popular instantiation, *ResNet-50* (with ∼25 million parameters), as the default CNN architecture. To train CNNs on ImageNet, we follow the standard recipe of [14, 30]. Specifically, we train all CNNs for a total of 100 epochs, using momentum-SGD optimizer; we set the initial learning rate to 0.1, and decrease the learning rate by 10× at the 30-th, 60-th, and 90-th epoch; no regularization except weight decay is applied.

Vision Transformer. ViT [11] successfully introduces Transformers from natural language processing to computer vision, achieving excellent performance on several visual benchmarks compared to CNNs. In this paper, we follow the training recipe of DeiT [41], which successfully trains ViT on ImageNet without any external data, and set *DeiT-S* (with ∼22 million parameters) as the default Transformer architecture. Specifically, we train all Transformers using AdamW optimizer [26]; we set the initial learning rate to 5e-4, and apply the cosine learning rate scheduler to decrease it; besides weight decay, we additionally adopt three data augmentation strategies (*i.e*., RandAug [8], MixUp [55] and CutMix [53]) to regularize training (otherwise Deit-S will attain significantly lower ImageNet accuracy due to overfitting [5]).

Note that different from the standard recipe of DeiT (which applies 300 training epochs by default), we hereby train Transformers only for a total of 100 epochs, *i.e*., same as the setup in ResNet. We also remove {Erasing, Stochastic Depth, Repeated Augmentation}, which were applied in the original DeiT framework, in this basic 100 epoch schedule, for preventing over-regularization in training. Such trained DeiT-S yields 76.8% top-1 ImageNet accuracy, which is similar to the ResNet-50's performance (76.3% top-1 ImageNet accuracy).

3.2 Robustness Evaluations

Our experiments mainly consider two types of robustness here, *i.e*., robustness on adversarial examples and robustness on out-of-distribution samples.

Adversarial examples, which are crafted by adding human-imperceptible perturbations or small-sized patches to images, can lead deep neural networks to make wrong predictions. In addition to the very popular PGD attack [27], our robustness evaluation suite also contains: A) AutoAttack [7], which is an ensemble of diverse attacks (*i.e*., two variants of PGD attack, FAB attack [6] and Square Attack [1]) and is parameter-free; and B) Texture Patch Attack (TPA) [50], which uses a predefined texture dictionary of patches to fool deep neural networks.

Recently, several benchmarks of **out-of-distribution samples** have been proposed to evaluate how deep neural networks perform when testing out of the box. Particularly, our robustness evaluation suite contains three such benchmarks: A) ImageNet-A [18], which are real-world images but from some challenging scenarios (*e.g*., occlusion and fog scene) for recognition; B) ImageNet-C [16], which is designed for measuring network robustness to 75 distinct common image corruptions; and C) Stylized-ImageNet [12], which creates texture-shape cue conflicting stimuli by removing local texture cues while retaining global shape information on natural images.

4 Adversarial Robustness

In this section, we first investigate the robustness of Transformers and CNNs on defending against adversarial attacks. We consider both perturbation-based attacks (*i.e*., PGD and AutoAttack) and patch-based attacks (*i.e*., TPA) in this evaluation scenario.

4.1 Robustness to AutoAttack

Following [35], we first report robustness of ResNet-50 and DeiT-Small under AutoAttack. Similar to previous findings, vision Transformer achieves higher accuracy when applying a small attacking radius ϵ = 0.001 while maintains similar clean accuracy on ImageNet as shown in Table 1.

However, when increasing the attack radius to 4/255, a more challenging but popular case [34, 46, 47], both architectures show **zero defense ability**. This observation motivates us to perform adversarial training [13, 27], an efficient way to increase the models ability to defense against adversarial attacks, on both those architectures for a further study on their robustness.

Table 1: Top-1 accuracy of ResNet-50 and DeiT-S on defending against AutoAttack with different perturbation radius, using ImageNet val dataset.

	Clean	Attack radius	
	acc	0.001	4/255
ResNet-50	76.9	17.8	0
DeiT-S	76.8	22.1	0

4.2 Adversarial Training

We conduct adversarial training on DeiT-small and ResNet-50. Specifically, adversarial training [13, 27], aims to optimize the framework below by training networks with adversarial examples that generated on-the-fly:

$$_{\theta}\mathbb{E}_{(x,y)\sim\mathbb{D}}\left[\max_{\epsilon\in\mathbb{S}} L(\theta, x+\epsilon, y)\right], \tag{1}$$

where $\mathbb{D}$ is the underlying data distribution, $L(\cdot,\cdot,\cdot)$ is the loss function, θ is the network parameter, x is a training sample with the ground-truth label y, ϵ is the added adversarial perturbation, and $\mathbb{S}$ is the allowed perturbation range.

4.2.1 Adversarial Training on Transformers

Following the default training strategy of DeiT, we carry out the adversarial training, which aims to train the network on adversarially perturbed images to increase the robustness.

We apply the PGD attacker [27] to generate adversarial perturbations ϵ. PGD performs a gradient descent step iteratively in the loss function w.r.t. the image pixel values based on an adversarially selected output target. Then it projects the resulting perturbed images into the feasible solution space within a maximum per-pixel perturbation of ϵ of the clean image, subject to an L_∞ constraint. Following [48, 33, 46], we select the cheapest version of PGD, *single-step PGD* (PGD-1), to lower the training cost. And we set the maximum per-pixel change $\epsilon = 4$ and the attack step size $\beta = 4$. No regularization except a weight decay of 0.05 is applied.

Interestingly, directly applying adversarial training to DeiT does not work—the model collapses and leads to only 4% robustness accuracy against PGD-5. We solve this problem by gradually increasing the training images' difficulty to provide a warm up with the learning rate, as show in Figure 1. This help stabilize the initial adversarial training process of Vision Transformer, and further leads to 44% of robustness accuracy of PGD-5.

This problem would not happen if simply applying to Transformer ResNet's adversarial training recipe that uses SGD optimizer with step learning rate schedule with no further augmentations, as previous work's setting[35]. But this recipe that crafted for ResNet would impair Transformers performance by a large range. According to our experiments the clean accuracy decreases to 59.9%(**-6.6%**), and PGD-100 robustness to 31.9%(**-8.4%**).

This sub-optimal results under SGD optimizer is expected. Liu *et al*. [24] gives an explanation on why standard SGD fails in training Transformers. As observed in [24], adaptive optimizers is capable of assign different learning rates to different parameters and lead to consistent update magnitudes even with unbalanced gradients. This is crucial since gradients of all attention modules in Transformers are unbalanced. Therefore, SGD is not suitable for training Transformers, under both vanilla and adversarial training setting.

(a) Epoch = 0 (b) Epoch = 4 (c) Epoch = 9

Figure 1: The illustration of augmentations applied when epoch=0, 4 and 9, showing how we progressively increase augmentation strength as a warm-up for adversarial training.

As discussed in many works before that AdamW is better for Transformer's vanilla training, adversarial training shows similar signals. Further more, augmentations including RandAug, MixUp and CutMix are also critical for adversarial training to prevent overfitting, as we have observed.

Aligning ResNet to DeiT As discussed above, *completely* following ResNet's training recipe seems to impair the performance of DeiT. Similarly for ResNet-50, if changed to AdamW optimizer, we observed that adversarial training process will collapse. And if applied with extra augmentations, both ResNet-50's clean accuracy and PGD robustness will suffers as well. More details will be provided in the supplementary materials.

However, some training technique in DeiT can still help the ResNet's adversarial training. According to the experiments in [47], activation function plays an important role in adversarial training. DeiT uses GELU as an activation function, while ResNet uses ReLU. In Table 2, experiments show that after properly applying GELU as activation function to ResNet-50, ResNet's adversarial training can lead to both higher clean accuracy and robustness compared with same settings with ReLU.

Main Results We show that in Table 2, after adversarial training, ResNet-50 can outperform DeiT-Small on ImageNet clean accuracy by 0.9% while have exactly the same robustness on defending against PGD attacks and AutoAttacks under the same 4/255 attack radius, challenging previous conclusions that Transformers are more robust than CNNs. We also re-evaluate their robustness to AutoAttack under radius 0.001 on adversarially trained model. After changing to GELU, ResNet-50's defense success rate increases from 62.2% to 65.7% (+2.5%), surpass DeiT-Small's 64.8% robustness by 0.9%.

Table 2: After aligning ResNet with DeiT' activation function GELU, ResNet-50 shows better accuracy (%) on ImageNet and while maintains the same robustness under adversarial attacks.

	Activation	Clean Acc	PGD-5	PGD-10	PGD-50	PGD-100	AutoAttack-4/255
ResNet-50	ReLU	66.8	38.7	34.2	32.5	32.3	26.4
	GELU	**67.4**	44.0	41.0	40.3	40.3	35.5
DeiT-Small	GELU	66.5	44.0	41.0	40.3	40.3	35.5

4.3 Robustness to PatchAttack

Since Autoattack is composed with one patch based attack, we further study the robustness with a more advanced patch attackers, named Texture Patch Attack (TPA) [50]. For TPA, we set the number of patches to 4 and the total area to 10% of the image area by default. With the number of patch increases, the difficulty of the TPA grows as well. We mainly evaluate non-targeted attacks of TPA.

Table 3 shows both clean accuracy on ImageNet and the defense success rate to TPA of ResNet-50 under different augmentation techniques used in DeiT. Compared to the original ResNet-50, all augmentation improve the robustness to patch attacks. But interestingly, we note observe that CutMix is extremely effective to improve the robustness of TPA, *i.e.*, CutMix only can subtantially improve model robustness against TPA by 29.4%.

Table 3: Defense success rate (%) of ResNet-50 with different augmentations against Patch Attacks. We also show clean accuracy on ImageNet(%).

Augmentations			ImageNet ↑	Patch Attack ↑
RandAug	MixUp	CutMix		
✗	✗	✗	78.9	19.7
✓	✓	✓	76.4	+28.9
✓	✓	✗	75.7	+12.0
✓	✗	✓	76.7	**+32.7**
✗	✓	✓	77.1	+20.1
✓	✗	✗	77.5	+4.6
✗	✓	✗	75.9	+11.8
✗	✗	✓	77.2	+29.4

The strongest performance for defending against TPA can be achieved by training with both CutMix and RandAug. In Table 4, we provide the comparison of the robustness to stronger patch attacks (*i.e.*, by increasing patch number from 4 to 10) between ResNet-50 and DeiT-Small under this setting. We can observe that ResNet is more robust to different levels of TPA compared with DeiT.

Table 4: Defense success rate (%) of ResNet-50 and DeiT-Small against Patch Attacks with different patch number. We also show clean accuracy(%).

Architecture	ImageNet↑	Patch Attack↑	
		P=4	P=10
ResNet-50	76.7	**52.4**	**34.5**
DeiT-Small	76.8	47.7	28.9

5 Generalization on Out-of-distribution Samples

In this section we evaluate the robustness to out-of-distribution samples of DeiT to ResNet models. As aforementioned, the training frameworks applied to Transformers and CNNs varies in many aspects, *e.g.*, training epochs, optimizers, learning rate schedule, augmentations *etc*. To capture different aspects of robustness, we rely on different, specialized benchmarks including ImageNet-A, ImageNet-C, and Stylized ImageNet.

5.1 Aligned Setting Comparison

We first provide a direct comparison between DeiT and ResNet in their original setting. In addition, for a more fair comparison, we fully align to ResNet-50 DeiT's training strategies, whose details can be found in Section 3.1. We denote this model as ResNet50*.

Experiments in Table 5 show that DeiT-Small has better generalization on the out-of-distribution samples, compared with both ResNet-50's original setting and aligned setting ResNet-50*.

Table 5: DeiT-Small has better generalization ability on ImageNet-C, ImageNet-A and Stylized-ImageNet. For ImageNet, ImageNet-A and Stylized ImageNet, results show Top-1 accuracy (%). For ImageNet-C, results show mCE (%, mean corruption error, lower is better).

Architecture	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Stylized-ImageNet ↑
ResNet-50	76.9	3.2	57.9	8.3
ResNet-50*	76.3	4.5	55.6	8.2
DeiT-Small	76.8	**12.2**	**48.0**	**13.0**

5.2 Best Setting Comparison

Considering the fair comparison and the more advanced training strategies used in DeiT, we first provide the results on fully aligned settings. However, this strategy crafted for DeiT may not benefit ResNet-50 the most. Therefore, we study those settings step-by-step and provide a best setting for ResNet-50 and DeiT-Small as another comparison.

5.2.1 Optimizers and Learning Rate Scheduler

In previous studies of the robustness comparison between ResNet and DeiT, optimizers and learning rate scheduler are not aligned. Here we study which is best for ResNet and under its best setting, if ResNet is comparable with DeiT.

Experiment Setting ResNet uses SGD in the standard training, while DeiT used AdamW with cosine learning rate. We report the generalization results on both those settings.

Main Results Table 6 shows with SGD and cosine learning rate scheduler, ResNet-50 has better generalization to those datasets. Therefore, in later experiments, without extra mentions, we'll keep this setting. But even under the best setting, DeiT-Small still leads by a large margin.

Table 6: The generalization of ResNet-50 under different optimizer and learning rate scheduler compared with DeiT.

	Optimizer	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Sty-ImageNet ↑
ResNet-50	SGD-Step	76.9	3.2	57.9	8.3
	SGD-Cosine	**77.4**	3.3	56.9	8.4
	AdamW	76.4	3.1	59.3	8.1
DeiT-Small	AdamW	76.8	**12.2**	**48.0**	**13.0**

5.2.2 Augmentations

Experiments show that augmentations are beneficial to the robustness on out-of-distribution samples, such as ImageNet-A and ImageNet-C. DeiT uses many augmentations, including RandAug, MixUp and CutMix, which may potentially increase its robustness. Therefore, we apply the same augmentations to ResNet as well.

Experiment Setting Here we stick to SGD as optimizer with cosine learning rate schedule, which works the best for ResNet-50 as aforementioned, and apply different combinations of the augmentation strategies used in DeiT.

Main Results As is shown in Table 7, after applying the augmentations, the generalization ability of ResNet-50 on distorted ImageNet datasets has improved a lot. In general, RandAug with MixUp shows the best improvements. However, there still exist some gap compared with DeiT-Small.

Table 7: DeiT shows better generalization compared with ResNet under different augmentations.

Architecture	Augmentations			ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Sty-ImageNet↑
	RandAug	MixUp	CutMix				
ResNet-50	✗	✗	✗	77.4	3.3	56.9	8.4
	✓	✓	✓	76.4	5.5	54.0	9.1
	✓	✓	✗	75.7	**6.3**	**52.3**	**10.8**
	✓	✗	✓	76.7	6.3	56.3	7.1
	✗	✓	✓	77.1	6.1	55.1	8.8
DeiT-Small	✓	✓	✓	**76.8**	**12.2**	**48.0**	**13.0**

5.2.3 Results of Best Setting Comparison

Therefore, after fully analyzing those settings step-by-step, we are able to provide a comparison between these two architectures under their best setting. DeiT-Small shows better generalization on out-of-distribution data in all those three dataset by a large margin under the best setting. The best setting we find for ResNet is SGD optimizer with cosine learning rate scheduler, applied with RandAug and MixUp. And we'll later refer to it as ResNet-Best.

5.3 The Model Size

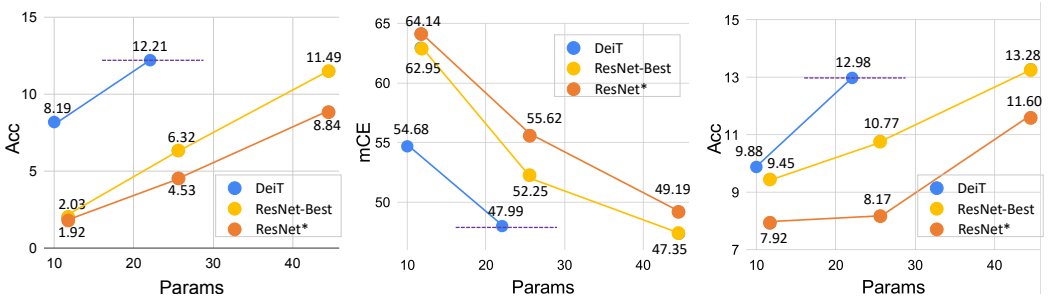
In order to better understand and compare DeiT and ResNets, we evaluate a range of models from each architecture family to study this two archtectures' robustness under different model size.

Table 8: DeiT shows better generalization ability compared with ResNet-50 under best settings.

Architecture	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Stylized-ImageNet ↑
ResNet-50	75.7	6.3	52.3	10.8
DeiT-Small	76.8	**12.2**	**48.0**	**13.0**

Experiment Setting As aforementioned, ResNet-50 and DeiT-Small has similar parameters. However, for a smaller model ResNet-18, the original DeiT model family do not contain one with similar parameters. Therefore, in order to make a fair comparison with , we follow the designing rule of DeiT, and set up a model with similar parameters as ResNet-18, namely DeiT-Mini, whose embedding dimension is 256 and number of head is 4, between DeiT-Tiny and DeiT-Small.

Main Results From Figure 2 we can observe that both DeiT models show better robustness compared with ResNet models with similar model size under their best settings. Moreover, we further increase ResNet's model size to ResNet-101. After the capacity of ResNet grows to twice its size, it is now compatible with DeiT-Small.



(a) ImageNet-A (b) ImageNet-C (c) Stylized-ImageNet

Figure 2: DeiT models show better generalization ability compared with ResNet models with different model sizes on ImageNet-A, ImageNet-C and Stylized-ImageNet.

5.4 Distillation

In the previous sections, we make comparison of ResNet-50 and DeiT-Small under aligned setting and best setting seperately. Here, we provide another comparison with the help of knowledge distillation. By analyzing the generalization difference between teacher model and student model, which learns from the passed knowledge its teacher model, we can further explore the generalization difference between these two different architectures.

Experiment Setting We design two sets of experiments. In the first set, we use ResNet-50 as a teacher model to distill DeiT-Small; in the second, Deit-Small as the teacher model to distill ResNet-50. We perform soft distillation following[19], which minimizes the Kullback-Leibler divergence between the softmax of the teacher and the softmax of the student model. During distillation, our training strategy remains consistent with DeiT-Small setting, same as the setting in Section 5.1.

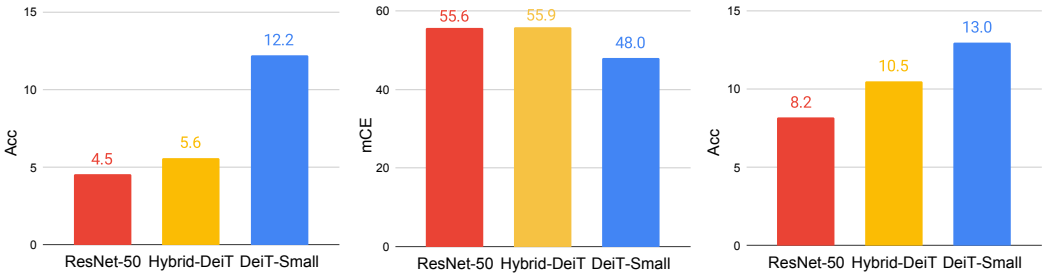
Main Results In the first set, after distilling with ResNet-50's knowledge, DeiT-Small achieves higher generalization on ImageNet-A, ImageNet-C and Stylized-ImageNet, by a large margin. However, in the second set, it is counter-intuitive that after using DeiT-Small as teacher model, the student model, distilled ResNet-50, is actually performing worse. This suggest that the generalization robustness of DeiT is rooted in the structure of Transformer that cannot be passed to ResNet via knowledge distillation.

5.5 Hybrid Architecture

As discussed above, DeiT architecture shows great generalization ability on out-of-distribution data by a large margin compared to ResNet models. In order to further validate whether this robustness is

Table 9: Generalization ability of ResNet-50, DeiT-Small and their distilled models.

Distillation	Architecture	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Stylized-ImageNet ↑
Teacher	ResNet-50*	76.3	4.5	55.6	8.2
Student	DeiT-Small-Distill	76.2	10.9 (+6.4)	49.3 (-6.3)	11.9 (+3.7)
Teacher	DeiT-Small	76.8	12.2	48.0	13.0
Student	ResNet-50*-Distill	76.7	5.2 (-7.0)	54.2 (+6.2)	9.8 (-3.2)



(a) ImageNet-A (b) ImageNet-C (c) Stylized-ImageNet

Figure 3: Transformer blocks show better generalization compared with ResNet structures.

brought by the architecture of Transformers, we introduce Transformer block to ResNet structure as hybrid model and analyze its generalization ability.

Experiment Setting We follow the basic rule of ViT's design for hybrid model, in which the patch embedding projection is applied to patches extracted from a CNN feature map. In our case, we take the output of stage 4 of a regular ResNet-18 and then feed the intermediate feature maps into DeiT-Mini. The choice of those two structures are meant to keep the model size of original and the hybrid at the same level. Under our setting, hybrid-DeiT contains ~21 million parameters, which is in the same scale with ResNet-50 (~25 million parameters) and DeiT-Small (~22 million parameters). Noe that all those models are trained following the DeiT recipe, same as the setting in Section 5.1.

Main Results Figure 3 shows the generalization on out-of-distribution samples of ResNet-50, DeiT-Small and Hybrid-DeiT on ImageNet-A, ImageNet-C and Stylized ImageNet, respectively. We note that, with the introduction of Transformer block, this hybrid stucture's robustness increases in general compared with ResNet-50—with 1.1% growth on ImageNet-A top-1 accuracy and 2.5% growth on Stylized-ImageNet, while maintains similar mCE on ImageNet-C. However, if compared with DeiT-Small, which is composed of purely Transformer blocks, hybrid structure's generalization robustness is still lower by a large margin. Therefore, we can conclude that the Transformer block do imply more generalization robustness.

5.6 300-Epoch Training

As aforementioned, 100-epoch setting is able to provide a fair comparison under similar number of parameters and a similar top-1 accuracy on ImageNet classification with less computational budget. Nevertheless, we are also interested in the longer training set-up, to further understand and compare the robustness of these two structures.

From Table 10, though we can still observe that the Transformer shows much stronger generalization than the CNN on out-of-distribution samples, we argue that such setup is less interesting and a little bit unfair—DeiT-Small shows much better accuracy than ResNet-50 on ImageNet classification, therefore it is expected that DeiT-Small will also show stronger robustness generalization than ResNet-50 on out-of-distribution samples.

To make the setup fairer (i.e., comparing the robustness of models that have similar accuracy), we now compare the robustness generalization between DeiT-Small and ResNet-101. The results are as the following (%) in Table 11. We can observe that though ResNet-101 and DeiT-Small achieve

Table 10: DeiT-S shows better generalization ability under 300-epoch setting compared with Res-50.

Architecture	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Stylized-ImageNet ↑
ResNet-50	78.1	8.8	50.3	9.5
DeiT-Small	79.9	**19.2**	**42.8**	**15.1**

similar accuracy on ImageNet, DeiT-Small demonstrates much stronger robustness generalization than ResNet-101. We further scale this setup by comparing DeiT-Base and ResNet-152.

Table 11: DeiT-S shows better generalization ability under similar accuracy with Res-101.

Architecture	ImageNet ↑	ImageNet-A ↑	ImageNet-C ↓	Stylized-ImageNet ↑
ResNet-101	80.2	17.6	45.8	11.9
DeiT-Small	79.9	**19.2**	**42.8**	**15.1**
ResNet-152	81.2	21.3	42.1	12.3
DeiT-Base	81.8	**27.9**	**38.0**	**17.9**

In summary, in this 300 training epoch setup, the same conclusion is drawn as 100-epoch setup that Transformers are much more robust than CNNs on out-of-distribution samples.

6 Conclusion

With the recent success of Vision Transformer on recognition tasks, researchers begin to study its robustness compared with traditional CNNs. While many recent works suggest that Transformers are much more robust than CNNs, their comparisons are not fair in many aspects, *e.g.*, training datasets, model scales, training strategies, *etc*. Therefore, we believe that such conclusion cannot be drawn based on these settings, which motivates us to provide a fair and in-depth comparisons between these two architectures. With our unified training setup, we found that Transformers are no more robust than CNNs regarding adversarial robustness. And if properly aligned, CNNs can achieve exactly the same robustness as Transformers on defending against adversarial attacks, including PGD attacks, AutoAttack and Texture Patch Attack. While regarding generalization on out-of-distribution samples (*e.g.*, ImageNet-A, ImageNet-C and Stylized ImageNet), we find pre-training on (external) large-scale datasets is not a necessary condition for letting Transformers show strong performance than CNNs. Additionally, we find adopting self-attention-like architectures is crucial for generalization robustness. We hope this work would shed lights on the understanding of Vision Transformer and the robustness between Transformers and CNNs.

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