Demystify Transformers & Convolutions in Modern Image Deep Networks

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Abstract—Vision transformers have gained popularity recently, leading to the development of new vision backbones with improved features and consistent performance gains. However, these advancements are not solely attributable to novel feature transformation designs; certain benefits also arise from advanced network-level and block-level architectures. This paper aims to identify the real gains of popular convolution and attention operators through a detailed study. We find that the key difference among these feature transformation modules, such as attention or convolution, lies in their spatial feature aggregation approach, known as the “spatial token mixer” (STM). To facilitate an impartial comparison, we introduce a unified architecture to neutralize the impact of divergent network-level and block-level designs. Subsequently, various STMs are integrated into this unified framework for comprehensive comparative analysis. Our experiments on various tasks and an analysis of inductive bias show a significant performance boost due to advanced network-level and block-level designs, but performance differences persist among different STMs. Our detailed analysis also reveals various findings about different STMs, such as effective receptive fields and invariance tests. All models and codes used in this study are publicly available at https://github.com/OpenGVLab/STM-Evaluation.

Index Terms—Spatial token mixer, transformer, CNN, and image deep network.

1 INTRODUCTION

Vision transformers [1] have revolutionized the landscape of visual backbone models, inspiring a set of deep networks incorporating attention [2], [3], [4], convolution [5], [6], [7], and hybrid [8], [9] blocks. These networks consistently demonstrate performance gains attributed to novel feature transformation operators. However, it is essential to acknowledge the potential influence of advanced network engineering techniques, including macro architecture design [10] and training recipes [3], [5], [11]. This broader context prompts a critical question that do the observed performance gains primarily stem from novel operator designs or from the adoption of advanced network engineering techniques?

To address this inquiry, we conduct a comprehensive survey of recent vision backbones featuring novel operators [2], [3], [4], [5], [13]. Our examination reveals that the distinctions among these operators, and their asserted novelty, primarily hinge on the approach to spatial feature aggregation, commonly referred to as the Spatial Token Mixer (STM). Notably, our scrutiny aligns with the broader interest in understanding the true efficacy of STMs. A recent study, MetaFormer [10], underscores the significance of transformer block design in overall performance. Remarkably, MetaFormer demonstrates that the STM within the transformer block, specifically the attention layer, can be substituted with a simple mixing operation, such as pooling, without a substantial drop in performance. This finding serves as an additional motivation for our investigation into the authentic performance gains associated with various STMs, aiming to discover any potential biases arising from disparate network engineering practices.

To achieve this, we first construct a modern and unified
architecture for comparison, where we sequentially determine the stage-level design (i.e., stem and transition layers) and block-level design (i.e., the topology of basic blocks) by a series of experiments and analyses. We find that some macro designs such as different downsampling operations may affect the performances for a certain type of STM, and the proper block design can also contribute to performance gain significantly. We combine the findings and beneficial designs into a unified architecture. By instantiating different STMs on this architecture, we achieve comparable or even better results than the reported performance in their original papers, as shown in Fig. 1. Our study includes four pivotal STMs representing diverse approaches in vision backbones: local attention [2], [3], global attention [4], depth-wise convolution [5], and dynamic convolution [14]. Refer to Fig. 2 for a visual overview of these operations. Each STM is selected for distinct characteristics, ensuring a thorough exploration of spatial feature aggregation in the unified architecture.

Employing the instantiated models, we conduct an investigation and comparison of STMs across multiple dimensions. Initially, we assess the performance of different models on both upstream (classification) and downstream (object detection) tasks, using ImageNet-1k [15] and COCO [16] datasets. Our findings, as illustrated in Fig. 1, reveal performance gaps among various STMs, deviating from reported trends with original implementations. Notably, earlier STMs, imbued with advanced design principles, achieve comparable or superior performance compared to recent counterparts in both upstream and downstream tasks. Furthermore, STMs exhibiting vision-specific inductive bias and dynamic information modeling mechanisms, such as local attention and dynamic convolution, demonstrate relatively robust performance. Static convolution proves effective in low-capacity models (around 4.5M parameters) but lags behind larger-scale models. Additionally, we observe that the inter-window information transfer in local-attention STMs significantly influences performance.

Moreover, our aim extends beyond performance comparison to uncover distinctive characteristics in different STMs. The design of an STM, reflecting prior knowledge and constraints in the hypothesis space (inductive bias), is analyzed for its impact on learned model characteristics, including locality, shift, rotation, and scale invariance. Observations reveal significant variations among STMs in capturing information during feature aggregation, termed as the effective receptive field (ERF) [17]. Further exploration highlights that a larger ERF does not guarantee improved performances, and the benefits may saturate as the model scales up. In our invariance test, models exhibiting superior performance also demonstrate heightened robustness against variations, suggesting the learnability of invariance through data and diverse augmentations. Additionally, static convolution, employing weight-sharing and emphasizing locality, demonstrates more pronounced translation invariance. Notably, leveraging a flexible sampling strategy for dynamic aggregation, dynamic convolution (DCNv3 [14]) outperforms other STMs in rotation and scaling invariance.

Our contributions can be summarized as follows:

- We experimentally compare typical spatial token mixers, unveiling the characteristics of local attention, global attention, depth-wise convolution, and dynamic convolution.
- Distilling effective network engineering techniques from modern backbone designs, we create a unified architecture that enhances spatial token mixer performance compared to their original implementations.
- Our experiments using the unified architecture on image classification and object detection tasks reveal significant performance improvements due to network engineering techniques. Despite this, performance gaps persist among different STMs, with the earlier halo attention achieving state-of-the-art results.
- Analyzing the impact of inductive bias on STM characteristics, we challenge the notion that the effective receptive field alone is a metric for evaluating STM quality. Our findings underscore that STMs with strong
Notably, Han et al. to more advanced network engineering designs [5], [6], and dense connections [25], grouping techniques [26], [27], and channel attention [28]. In contrast, spatial feature aggregations, parameter sharing, and translation equivalence [20], [21], [22], demonstrated that introducing flexible point sampling and long-range dependence mechanisms received less attention. Approaches like channel attention [28]. In contrast, spatial feature aggregations, parameter sharing, and translation equivalence [20], [21], [22], demonstrated that introducing flexible point sampling and long-range dependence, breaking the locality constraint. With the emergence of vision transformers [1], convolution has earlier occupied vision backbones [21], [22], [23]. The evolution of vision backbones primarily centered on architectural aspects, including residual learning [24], dense connections [25], grouping techniques [26], [27], and channel attention [28]. In contrast, spatial feature aggregation mechanisms received less attention. Approaches like deformable convolution [29] and non-local methods [30] introduced flexible point sampling and long-range dependency, breaking the locality constraint. With the emergence of vision transformers [1], convolution has adapted to more advanced network engineering designs [5], [6], [7]. Notably, Han et al. [19] demonstrated that introducing dynamic weight computation into depth-wise convolution can achieve comparable or slightly superior performance compared to local vision transformers.

2 RELATED WORK

2.1 Convolution-Based Spatial Token Mixers

Leveraging image-specific priors, such as sparse interactions, parameter sharing, and translation equivalence [20], convolution has earlier occupied vision backbones [21], [22], [23]. The evolution of vision backbones primarily centered on architectural aspects, including residual learning [24], dense connections [25], grouping techniques [26], [27], and channel attention [28]. In contrast, spatial feature aggregation mechanisms received less attention. Approaches like deformable convolution [29] and non-local methods [30] introduced flexible point sampling and long-range dependency, breaking the locality constraint. With the emergence of vision transformers [1], convolution has adapted to more advanced network engineering designs [5], [6], [7]. Notably, Han et al. [19] demonstrated that introducing dynamic weight computation into depth-wise convolution can achieve comparable or slightly superior performance compared to local vision transformers.

2.2 Attention-Based Spatial Token Mixers

Since the introduction of the transformer into vision [1], its core operator, attention, has significantly challenged the dominance of convolution. Unlike standard convolution, attention boasts a global receptive field and dynamic spatial aggregation. However, the dense attention calculation comes with a substantial computational overhead, scaling quadratically with the size of input maps. This becomes particularly impractical for applying vanilla attention to feature pyramids, especially on large feature maps. Consequently, attention operators in vision typically reduce the number of locations attended during attention calculation. Approaches like PVT [4], [18] and Linformer [31] employ global attention on down-sampled feature maps, while Pale Transformer [32] uses pale operation to sample features across the entire feature map. Drawing inspiration from the locality prior of convolution, local attention is introduced [2], [3], where attention is constrained within local windows. Since these local windows are non-overlapping, mechanisms for inter-window information transfer, such as “haloing” [2] and shifted windows [3], have been developed.

2.3 Optimizing Engineering and Backbone Evaluation

Instead of introducing novel spatial token mixers, some research focuses on identifying advantageous network engineering techniques. ResNet-RSB [33] demonstrates that an advanced training recipe can significantly enhance performance compared to a naive setting. ConvNeXt [5] modernizes a standard ResNet by incorporating recent advancements in both training recipes and network architecture design. MetaFormer [10] underscores the significant role of the abstracted architecture of the Transformer block in achieving competitive performance. Recent work by Yu et al. [34] further validates the effectiveness of Transformer-style block design, achieving impressive performance using basic or common mixers. Despite MetaFormer’s emphasis on the importance of the transformer block, diverting attention from STMs, we observe performance gaps among different STMs. Toolkit initiatives like Timm [35] offer off-the-shelf or reproduced models but lack a comprehensive comparison of different STMs under a unified architecture. As depicted in Fig. 1, an advanced STM design, such as halo-attention, coupled with a modern network architecture, outperforms other STMs with the same architecture by a significant margin. Additionally, we find that network engineering techniques extend beyond block-level design. We conduct more ablation studies on stage-level design and compare them with ConvNeXt’s block design. It’s important to note that our primary goal is not to construct an extremely optimized framework but to comprehensively compare and analyze different STMs under a unified setting from various perspectives.

3 SPATIAL TOKEN MIXER

3.1 Definition of Spatial Token Mixer

The Spatial Token Mixer (STM) aims to aggregate spatial features around each pixel to transfer contextual information. Given an input feature map $X \in \mathbb{R}^{C \times H \times W}$, we define the token mixing function $\mathcal{M}$ for the mixing target point $p$ as:

$$\mathcal{M}(p) = W_o \sum_{k \in S} w_{pk} \cdot X(k),$$

(1)

where $S$ denotes the sampling point set that records the pixels to attend; $w_{pk}$ denotes the aggregation weight with respect to the sample point $p$; and $W_o$ is the output projection matrix. In practice, STMs typically employ a multi-head strategy, projecting or splitting the input feature into different heads.

STMs vary in the generation of the sampling point set and the aggregation weight, as summarized in Table 1. In this study, we consider four prevalent types of STMs for comparison: depth-wise convolution, dynamic convolution, local attention, and global attention.
3.2 Taxonomy of Spatial Token Mixer

3.2.1 Depth-Wise Convolution

Depth-wise convolution aggregates features in an input-independent manner. The sampling point set consists of sliding windows centered at the mixing target point \( p \), and the aggregation weight is represented by a learnable weight matrix—the convolution kernel. Despite its simplicity, recent convolution networks [5], [6] have demonstrated that depth-wise convolution, when combined with advanced architecture and training recipes, can achieve comparable performance to top-performing vision transformers. In our comparison, we employ a 7 × 7 depth-wise convolution, following the configuration of DWNNet [19] and ConvNeXt [5]. Specifically, we incorporate input and output projection layers before and after the depth-wise convolution in our unified block design.

3.2.2 Dynamic Convolution

Dynamic convolution is input-dependent, where both the sampling point set and aggregation weights are generated conditioned on the inputs. For instance, the widely-used deformable convolution [14], [29], [36] infers per-pixel sampling point sets and aggregation weights from input features for spatial aggregation. In this comparison, we utilize deformable convolution v3 (DCNv3) from InternImage [14] as the representative example of dynamic convolution. We employ nine sampling points, consistent with the original implementation. The offsets and weights for these sampling points are determined through a 3 × 3 depth-wise convolution followed by a linear projection. Weights are normalized using a Softmax function.

3.2.3 Global Attention

Global attention-based STM mixes features across the entire spatial domain, with aggregation weights dynamically generated through the inner product between the target point and each sampling point. While global attention offers a theoretically global receptive field without introducing image-specific inductive bias like locality, it comes with a significant computational overhead that scales quadratically with input resolutions. To integrate global attention STMs into pyramid-like vision backbones, optimization for efficiency is essential. A common practice involves constraining the cardinality of the sampling point set [4], [13], [32]. In our experiments, we adopt spatial reduction attention from PVT [3]. During attention computation, the key and value feature maps are downsampled.

3.2.4 Local Attention

An alternative approach to optimizing global attention involves introducing locality, i.e., restricting the sampling point set to local windows [2], [3], rather than the entire spatial domain. Given the intricacy of attention, local attention, in contrast to the densely overlapped sliding windows in convolution, employs non-overlapping local windows where pixels within each window share the same sampling point set. To facilitate information transfer among different windows, HaloNet [2] enlarges each window with an additional band resembling a “halo.” Swin Transformer [3] introduces shifted windows to create overlapping sampling points, enabling information transfer between different blocks. For a comprehensive exploration of the design principles of local attention STMs, we include both halo attention from HaloNet and shifted window attention from Swin Transformer in our comparison.

4 Unified Architecture and Training Recipe

This section presents our unified architecture and training strategies. We systematically analyze the stage-level and block-level architecture design through sequential ablations. Subsequently, we instantiate different STMs discussed in Sec. 3 into the unified architecture for comprehensive comparison.
4.2 Block-Level Design

Block-level design determines the topology of operators, specifying their positions and connections. Before the emergence of vision transformers, most vision models adhere to the block design of standard ResNet [24], featuring a single skip connection with standard convolution (see the HaloNet block design in Fig.2). The transformer block [1], [12] introduces a distinct approach by segregating STM and channel feature transformation into two residual connections, each with a normalization layer (refer to the unified block design in Fig.2). Metaformer [10] demonstrates that the transformer-style block design itself significantly contributes to the performance gain of vision transformers.

Hence, for the unified architecture, we adopt a standard transformer block as depicted in Fig.2 and replace the attention with different types of STMs. In the right part of Table2, the unified block design substantially enhances the performance of HaloNet (+2.5%), which employs the ResNet-style block design in its original implementation. However, ConvNeXt [5] achieves comparable performance with depth-wise convolution using an improved ResNet block design (denoted as “original” in Table 2). This suggests that the transformer’s block design may not necessarily be a universal rule. Despite this, for the sake of uniformity in architecture for comparison, we continue to use the unified block design for all compared STMs, including depth-wise convolution. We further compare the compatibility of the ConvNeXt block and the transformer block for different STMs in Sec. 5.3. Here, we denote the overall network, where the depth-wise convolution used in the unified architecture, as “U-DWConv”.

4.3 Model Configuration and Training Strategies

4.3.1 Model Configuration

To facilitate a comprehensive comparison, we instantiate STMs on models with four different scales: micro (~4.5M), tiny (~30M), small (~50M), and base (~90M). Implementations under our unified architecture are denoted with the prefix “U-”. Parameters and MACs of different models are detailed in Table 4. It is worth noting that micro models, with only around 4.5M parameters, are seldom discussed for standard backbones. Given the differing complexities of various STMs, the blocks per stage and channel numbers also vary. Further details can be found in the supplementary material.

4.3.2 Image Classification

We consolidate training techniques from recent top-performing networks [3], [5] into a unified strategy. Models undergo 300 training epochs on ImageNet-1k [15] with the AdamW optimizer [37]. Training specifics include gradient clipping with a maximum norm of 5.0, weight decay of 0.05, layer scale [38] starting at $10^{-6}$, label smoothing [39] at 0.1, and stochastic depth [40]. Standard data augmentation practices [3], [5] are employed, incorporating RandAugment [41], Mixup [42], Cutmix [43], Random Erasing [44], and color jitter. Training settings are uniform across all models, except for batch size and drop path rate. Batch sizes are set to 1,024 for U-Swin Transformer, U-HaloNet, and U-PVT, and 4,096 for U-DWConv and U-InterImage, as larger batch sizes favor convolutional STMs. Drop path rates adhere to the original settings in their respective papers. The learning rate is determined as (batch size/1024) × $10^{-3}$ with a linear warm-up lasting 20 epochs and cosine decay. Refer to Table 3 for detailed parameters.

4.3.3 Object Detection

We employ object detection as the downstream task and integrate the models into Mask-RCNN [45] for evaluation. Models are trained and evaluated on COCO train2017 and val2017 with single-scale training and evaluation. Images are resized so that the shorter sides equal 800 pixels while the longer sides do not exceed 1,333 pixels. All models are trained using AdamW [37] for 12 epochs with a batch size of 16. The learning rate is set to $10^{-4}$ and drops by 10× at the eighth and tenth epochs. The weight decay is set to 0.05 and the warmup iterations are 1000. Drop path rates are set to 0.1, 0.2, 0.2, and 0.3 for micro, tiny, small, and base models, respectively.

5 Results and Discussion

5.1 Image Classification

We present the comparison of different STMs on ImageNet-1k classification in Table 4. U-InternImage achieves the best performance on tiny and small models but slightly falls behind U-HaloNet on micro and base scales. Halo-Attn demonstrates comparable performance with DCNv3 and outperforms SW-Attn in Swin Transformer significantly. This suggests that “haloing” is a practical window information transfer design for local-attention STMs when performance is a priority. It highlights that the relatively early STM, such as halo attention, can yield a significant
performance gain with advanced network engineering techniques. Using the $7 \times 7$ DW-Conv can achieve comparable performance with SW-Attn and surpasses SW-Attn on micro models. U-PVT with global attention (SR-Attn) as STM shows obvious advantages under small models but quickly becomes comparable with U-Swin Transformer on other scales.

### 5.2 Object Detection

We use object detection as the down-stream task to evaluate different STMs. Table 5 reports the detection results, where (i) STMs with high accuracy (Halo-Attn and DCNv3) retain the advantages on object detection and surpass the other STMs by large margins; (ii) global attention (U-PVT) performs the worst on micro models but becomes on par with SW-Attn on other scales; (iii) depth-wise convolution shows strong performance among the micro models, but is not competitive at larger scales. In our experiments, both local-attention- and convolution-based STMs with locality inductive bias perform better compared with the model using global spatial reduction attention.

### 5.3 Ablation Study of the Unified Architecture

In this section, we conduct an ablation study on the unified architecture design for STMs. As discussed in Sec.4.2, the $7 \times 7$ depth-wise convolution (DW-Conv) with the unified block design or ConvNeXt [5] block design yields similar performance. This raises the question of whether ConvNeXt’s block design can be an alternative to the transformer block design. Hence, we perform an ablation study for comparison, gradually transforming our unified architecture (A) into the ConvNeXt architecture (E).

As shown in Fig. 4, for the stage-level design, B shifts the layer normalization (LN) after the global average pooling in the decoder head based on A, and C removes LN after each stage based on B. For the block-level design, D adopts the block design of ConvNeXt (Fig.2(e)) based on A. Note that we keep our stem and transition layer (Fig.3) in all models.
Fig. 4. The illustration showcases five architectures, transitioning from our unified architecture (A) to the ConvNeXt architecture (E). The yellow shadings in architectures B-E emphasize their differences compared with architecture A.

| Methods                  | MACs | ImageNet-1k Acc |
|--------------------------|------|-----------------|
| U-Swin Transformer       | 9.16 | 83.3            |
| U-HaloNet                | 9.75 | 84.0            |
| U-HaloNet-Switch         | 9.45 | 83.9            |
| U-HaloNet-1px            | 9.32 | 83.8            |
| U-HaloNet-Shift          | 9.75 | 82.7            |

pattern, while Swin-Attn tends to aggregate information from a particular direction (see Fig. 6). To investigate the impact of these factors, we introduce three new variants for Halo-Attn, as shown in Table 7. First, U-HaloNet-Switch is added, conducting inter-window information transfer every two blocks. Next, we introduce U-HaloNet-1px, with a halo size set to one. Finally, we shift the query window of Halo-Attn to the top-left corner while keeping the total window size unchanged to examine the effect of non-central aggregation.

Our experimental results, presented in Table 7, demonstrate that the impact of window size and inter-window transfer frequency is not significant: halving the inter-window transfer frequency reduces MACs by 0.3G while still preserving performance, and reducing the halo size to one only results in a 0.2% accuracy drop. However, U-HaloNet-Shift shows a significant performance drop of 1.3% on accuracy, suggesting that the geometry of inter-window interaction is the crucial factor for local attention operators.

6 Inductive Bias and Invariant Analysis

In this section, we explore the impact of the inductive bias of various STMs on learned model characteristics. We conduct analyses on effective receptive fields, translation invariance, rotation invariance, and scaling invariance.
6.1 Effective Receptive Field

The effective receptive field (ERF) [17] of a unit in vision backbones refers to the region where the pixels influence the output of this unit. While the inductive bias introduced by different STMs sets the theoretical upper limit for the receptive field, the actual ERFs can vary. We employ the ERF toolbox [17] to assess the ERF of the center pixel in feature maps across different stages. Models trained on ImageNet-1k are used to compute the ERF maps. The ERF toolbox provides a gradient norm map, with each value indicating the impact of specific locations on the center point. By placing a gradually expanding window at the center, we determine the square length-to-input size ratio when the sum of the gradient norm within the window reaches 50% of the image size. This ratio, denoted as ERF@50, serves as the quantitative metric following [6].

We explore the relationship between Effective Receptive Field (ERF) and downstream performance in object detection. In Fig. 5, we present the box accuracy for small, medium, and large objects. Interestingly, we observe no strong correlation between ERF and detection accuracy. For instance, U-Net exhibits comparable detection accuracy with smaller ERFs compared to U-InternImage. In the case of base models, accuracy comparisons across different scales remain consistent, and performance appears uncorrelated with ERF sizes. Therefore, we posit that ERF should not serve as a definitive metric for evaluating STM quality. A smaller ERF does not necessarily imply inferiority compared to STMs with larger ERFs.

Furthermore, our observations indicate that the design of STMs influences the shape of the effective receptive field. Fig. 6 showcases visualized ERFs of SW-Attn and Halo-Attn. Notably, the shifted windows in the ERF of Swin-Attn are evident, with more features aggregated from the bottom-right corner, aligning with the direction of the shifted window. Conversely, halo attention exhibits a more symmetrical ERF due to the “halo” window information transfer. Additional results and visualizations of ERFs can be found in the supplementary material.

6.2 Invariance Analysis

In this subsection, we assess the robustness of different STMs under various geometric transformations. We specifically consider translation, rotation, and scaling for our analysis. Invariance can be inherent in the STM design, learned from training samples, or acquired through data augmentation. Convolution-based STMs inherently possess translation equivalence due to locality and weight sharing [20], while local-attention STMs maintain window-level translation equivalence. The translation equivalence closely relates to translation invariance, given that the feature map undergoes average pooling before entering the classifier in our case. Neither convolution-based nor attention-based STMs inherently incorporate inductive biases related to rotation or scaling.

6.2.1 Translation Invariance

Translation invariance refers to the model’s ability to maintain consistent outputs when input images undergo translation. We assess translation invariance in the classification task by introducing jitter to the images, ranging from 0 to 64 pixels. Following [47], we measure invariance by the probability that the model predicts the same label for the same input images when translated.

In the first row of Fig.7, we observe the translation invariance of different STMs, noting that: (i) Convolution-based STMs (DCNv3 and depth-wise convolution) exhibit better translation invariance (see the first row in Fig. 7 (a)). (ii) U-Draw-Net, utilizing global attention, performs the poorest in terms of translation invariance, likely due to the absence of translation equivalence. (iii) DCNv3 and halo attention consistently achieve the best performance even with translated images (see the first row in Fig. 7 (b)). (iv) Halo attention, depth-wise convolution, and DCNv3 demonstrate superior translation invariance initially, with DCNv3 improving its invariance during training (see the first row in Fig. 7 (c)).

6.2.2 Rotation Invariance

We evaluate rotation invariance on the classification task by rotating the images from 0° to 45° with a step of 5°. Similar to translation invariance, we measure prediction consistency under different rotation angles to assess the rotation invariance of different STMs.

From the second row in Fig. 7, we observe that: (i) DCNv3, with its input-dependent sampling strategy, exhibits strong robustness against rotation. (ii) Other STMs show comparable performance, with halo attention performing slightly better at larger rotation angles (> 30°). (iii) Rotation invariance is comparable among all STMs at the beginning of the training process, except for Halo-Attn, which demonstrates superior rotation invariance. However,
DCNv3 quickly learns strong rotation invariance from the training data.

6.2.3 Scaling Invariance

Scaling invariance is assessed in object detection by scaling input images with factors from 0.25 to 3.0 in steps of 0.25. Box consistency serves as the invariance metric, where predicted boxes on scaled images are reverted to the original resolutions. Subsequently, the boxes predicted at the original resolutions are employed as ground truth boxes to compute the box mAP.

From the third row in Fig. 7, we observe that: (i) All STMs are sensitive to downsampling and exhibit comparable invariance with the input in small sizes. (ii) DCNv3 performs better when upsampling the image, with both the box consistency and box mAPs outperforming the others. (iii) Halo-Attn shows comparable invariance with depth-wise convolution in the early training stage but learns better invariance in the last three epochs.

6.2.4 Summary

Considering the results from translation, rotation, and scale invariance, we can conclude that STMs with strong performance exhibit relatively high invariance. However, the design of STMs also contributes to invariance; for example, depth-wise convolution attains comparable translation invariance with Halo-Attn. Moreover, DCNv3, which learns to generate the sampling point set conditioned on inputs adaptively, achieves the best invariance among all the STMs. This suggests the generalization and robustness of DCNv3 compared to other STMs with fixed sampling sets.

7 CONCLUSION AND LIMITATIONS

In this study, we conducted a comparison of popular Spatial Token Mixers (STMs) within vision backbones, establishing a unified setting to isolate the impact of network engineering techniques. Through the distillation of successful network engineering strategies and the creation of a unified architecture via ablation studies, we integrate five representative STMs for thorough comparison. A series of experiments encompassing both upstream and downstream tasks are executed to scrutinize the influence of inductive bias on deep model learning. Our findings underscore the following key points: (i) the contribution of network engineering design is paramount to achieving performance gains, emphasizing the importance of thoughtful architecture choices; (ii) certain STMs, even those considered relatively early, can attain state-of-the-art performance when coupled with modern design principles.

This work endeavors to serve as a well-optimized platform for the development of new vision backbones, particularly those integrating advanced spatial feature aggregation mechanisms. The downstream task results and nuanced analyses yield valuable insights for practitioners, aiding them in the judicious selection of suitable backbones for their specific applications. While our study offers comprehensive insights, we acknowledge certain limitations and outline directions for future research. Our forthcoming work will focus on evaluating STMs within larger models and diverse datasets to bolster generalizability and robustness. Additionally, we plan to broaden the evaluation scope, encompassing a diverse range of downstream tasks, to provide a more thorough understanding of STM performance across various applications.

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