### Abstract

Vision Transformer (ViT) depends on properties similar to the inductive bias inherent in Convolutional Neural Networks to perform better on non-ultra-large scale datasets. In this paper, we propose an architecture called Efficiently lead Inductive biases to ViT (EIT), which can effectively lead the inductive biases to both phases of ViT. In the Patches Projection phase, a convolutional max-pooling structure is used to produce overlapping patches. In the Transformer Encoder phase, we design a novel inductive bias introduction structure called decreasing convolution, which is introduced parallel to the multi-headed attention module, by which the embedding’s different channels are processed respectively. In four popular small-scale datasets, compared with ViT, EIT has an accuracy improvement of 12.6% on average with fewer parameters and FLOPs. Compared with ResNet, EIT exhibits higher accuracy with only 17.7% parameters and fewer FLOPs. Finally, ablation studies show that the EIT is efficient and does not require position embedding. Code is coming soon: [https://github.com/MrHaiPi/EIT](https://github.com/MrHaiPi/EIT)

### 1. Introduction

In recent years, Transformer [16] has swept the field of natural language processing (NLP) due to its superior performance. The fields of the computer vision (CV) [3, 5, 20] and even the multi-agent reinforcement learning (MARL) [12, 17] are gradually infiltrated by it. Vision Transformer (ViT) [5] is the first CV model which is completely based on Transformer architecture and achieves better performance on ultra-large-scale image classification task compared with convolutional neural networks (CNN). ViT is also the first model trying to break the barrier of unifying the CV and NLP with the same backbone network and achieved a breakthrough. Specifically, ViT divides images into non-overlapping patches to correspond the tokens in NLP, and uses the full-transformer architecture to model the patches and complete the image classification task.

Although ViT has been successful in ultra-large-scale datasets, ViT is difficult to obtain the best performance compared with CNN (e.g., ResNet [7]) when trained on small-scale datasets. One possible reason is that transformer architecture lacks some of the properties similar to inductive biases (IB) inherent to CNN, such as translation equivariance and locality [5]. Many studies have been explored on introducing the IB into ViT, such as the locality-based methods like TNT [6] and T2T [25], or CNN based methods like LSRA [22], CvT [21] and ViT C [24]. Aforementioned researches have experimentally demonstrated that the introduction of IB can improve the performance of ViT. In summary, the current introduction of IB can be summarized in four ways, as shown in Fig.1. The first three approaches suffer from a significant increase in parameters and FLOPs, thus further introducing CNN’s hierarchical architecture in the final implementation. However, it destroys the structure of ViT and departs from the original intention of ViT that unifies CV and NLP by the same structure. The fourth approach does not introduce more parameters and FLOPs. Furthermore, both of the four approaches suffer from the same inefficient introduction of IB. The reason is that the input data of each layer’s MHA in both of the four approaches, which can be briefly expressed as \( x_i = MHA_i(\cdot) + ... \), all contain the data directly processed by some MHA of the front layer. The presence of each MHA weakens the IB of the whole equation and thus causes IB to weaken layer by layer.

This paper proposes a model called EIT, which can Efficiently lead the IB to the ViT without changing its backbone structure and with fewer parameters and FLOPs. Unlike the above four approaches that use the same structure at each layer, we propose a novel decreasing IB introduc-
Figure 1. Introduction of IB. (a) Data is pre-processed by IB structure [6] [25]. (b) MHA with built-in IB [21]. (c) MHA handles all data together with the module with IB structure [19]. (d) The MHA and the IB structure each process a invariant portion of the data [22]. (e) IB structure in the previous layer process less data than those in the next layer.

2. Related Work

Transformer [16] was a network architecture that relied deeply on a self-attentive mechanism to obtain global sensing capabilities. Since its introduction in machine translation tasks in 2017, Transformer had achieved state-of-the-art in many NLP tasks [4, 1]. Given this, researchers in the CV field had also applied Transformer to their research and achieved competitive results compared to CNN. Examples included image classification [3, 5], target detection [27], segmentation [18, 2], image enhancement [2], image generation [10], and video processing [20].

2.1. Vision Transformer

Although there were many Transformer-based models in the CV field, ViT [5] was the first model based entirely on Transformer and tried to unify the CV and NLP with the same network structure. In its implementation, ViT first split an image into non-overlapping patches, then mapped the patches into patches embedding by a linear mapping layer. Finally, it classified the images by connecting multiple standard TrEn. However, compared with CNN, the better performance of ViT relied heavily on ultra-large-scale datasets (e.g., ImageNet-21k and JFT-300M) with the reason lacking IB. In this paper, we study how to efficiently lead CNN’s inherent IB to ViT without changing its backbone structure. The ultimate goal is to improve its performance in small-scale datasets without breaking the uniformity of CV and NLP.

2.2. Lead Inductive Biases to ViT

Many methods have been proposed to lead IB to ViT. For example, Long-Short Range Attention (LSRA) [22] introduced Lite Transformer Block (LTB) to TrEn, which divided half of the data to be processed by MHA along the channel dimension to the convolutional layer. Transformer-in-Transformer (TNT) [6] introduced the transformer module inside patches as a way to model a more detailed pixel-level representation. Tokens-to-Token (T2T) [25] stitched together neighbouring embedding to form a new embed-
ulating that the network's performance will be further im-
proved if LSRA's deep layers is still small, so we believe that the
other words, the IB introduction of LSRA is more efficient
cause ViT
and thus has better performance. We believe this is be-
attention distances (head diversity), which ensures that each
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ViT without changing the backbone of ViT, we explored
3.1. Motivation
3. Our Approach
3.1. Motivation
In order to investigate the effect of IB introduction on ViT without changing the backbone of ViT, we explored the IB introduction in two phases of ViT using ViTC
and LSRA, and the results are shown in Fig[2]. The results show that the IB introduction improves the model’s performance, intuitively manifested in the increased diversity of head-attention distances (head diversity), which ensures that each layer has as many scales of attention distances as possible. The head diversity of LSRA is greater than that of ViTC
and thus has better performance. We believe this is be-
cause ViTC
only introduces IB at the very beginning of the model, while LSRA introduces IB throughout all TrEns. In other words, the IB introduction of LSRA is more efficient than that of ViTC
. However, we find that the head diversity of LSRA’s deep layers is still small, so we believe that the IB introduction of LSRA is not efficient enough. We speculated that the network’s performance will be further im-
proved if IB is introduced more efficiently to make the head diversity at the deep layers greater. To further improve the efficiency of IB introduction, we investigated why LSRA (Embedded Parallel) cannot bring IB to the leaning back layers.
3.2. Embedded Parallel
First, we give the short form of the expression for each layer of ViT. We ignore the operations (position embedding, class token and normalization), which do not affect the attention mechanism. For the input \( x_{i-1} \), the output \( x_i \) of ViT’s each \( L \) layers can be abbreviated as the following equation.

\[
\begin{align*}
    x_i &= x_{i-1} \\
    &+ \text{MHA}_i(x_{i-1}) + \text{MLP}_i(x_{i-1} + \text{MHA}_i(x_{i-1}))
\end{align*}
\]

(1)

We can understand the above equation as follows: \( x_{i-1} \) has IB of intensity \( \alpha_{i-1} \), then \( x_i \) has IB of intensity \( \beta_i\alpha_{i-1} \). Since the presence of MHA weakens the IB of the whole equation (MHA has an innate global attention mechanism), and MLP (fully-connection layer) does not enhance the IB of the whole equation (MLP does not fusion the different patches of the same channel), \( \beta_i \in [0, 1) \). This means that the IB intensity of \( x_i \) is weaker than that of \( x_{i-1} \).

If Embedded Parallel structure (convolution) is added, we can rewrite the Eq[1] as follow with ignoring the index of patches in \( x_i \) and the input of MLP.

\[
\begin{align*}
x_{i-1} &= x_{i-2} \\
&+ [\text{Conv}_{i-1}(x_{i-2}; C^c_{i-1})]; \text{MHA}_{i-1}(x_{i-2}[C^c_{i-1} ;]) \\
&+ \text{MLP}_{i-1} \\
x_i &= x_{i-1} \\
&+ [\text{Conv}_{i}(x_{i-1}; C^c_i)]; \text{MHA}_i (x_{i-1}[C^c_i ;]) \\
&+ \text{MLP}_i
\end{align*}
\]

(2)

where \( \text{Conv} \) stands for the convolution with some reshape operations, \( C^c_i \) is the channel number processed by \( \text{Conv} \). Due to the specificity of the convolution operation, \( \text{Conv} \) does not handle the class embedding. Since the network’s final output depends on class embedding, and MHA is the
only bridge between class embedding and other patches for data interaction, we can directly observe the IB introduction situation of MHA for each layer. If $C_{i}^c$ is the same for all layers, then the input of MHA, can be expressed as follows.

$$x_{i-1}[C_{i}^c] = x_{i-2}[C_{i}^c] + MHA_{i-1}(x_{i-2}[C_{i-1}^c]) + MLP_{i-1}[C_{i}^c]$$  \hfill (3)$$

It can be found that the Eq 1 and Eq 3 are formally the same. The only difference is that the MLP’s IB weakening for the entire equation is reduced due to the enhanced IB of the MLP input, but the IB at each layer is still weak. This means that the introduction of IB is not efficient when $C_{i}^c$ equals $C_{i-1}^c$. This explains why the head diversity in the deeper layers of the LSRA in Fig 2 does not increase. Although the above equation describes the inefficiency of introducing IB by LSRA (embedded parallel), this can be generalized to the other three methods (front, inside and parallel) of introducing IB (Fig 1). The only difference is the degree of weakening of IB by MLP in Eq 3. Our next goal is to find a way to enhance the IB of Eq 3.

### 3.3. Decreasing Embedded Parallel

We find that the IB of Eq 3 can be greatly enhanced with a small change: let $C_{i}^c$ be decreasing layer by layer (if $C_{i}^c$ is increasing, the situation is similar to Eq 3). The input of MHA in $C_{i}^c$ decreasing structure can be expressed as follows.

$$x_{i-1}[C_{i}^c] = x_{i-2}[C_{i}^c] + [Conv_{i-1}(x_{i-2}[C_{i}^c] ; C_{i-1}^c)] + MHA_{i-1}(x_{i-2}[C_{i-1}^c]) + MLP_{i-1}[C_{i}^c]$$  \hfill (4)$$

The Eq 4 differs significantly in form from Eq 3, specifically in that the above equation has the Conv shown in the second term. Furthermore, the input of Conv in Eq 4 which we can expand to get the following equation, has the IB with few weaken.

$$x_{i-2}[C_{i}^c : C_{i-1}^c] = x_{i-1}[C_{i}^c : C_{i-1}^c] + [Conv_{i-2}(x_{i-3}[C_{i}^c] ; C_{i-2}^c)] + MLP_{i-2}[C_{i}^c : C_{i-1}^c]$$  \hfill (5)$$

We can find that there is no longer an MHA operation displayed in Eq 5. The input $(x_{i-3}[C_{i}^c : C_{i-1}^c])$ to the Conv of Eq 5 and the first term $(x_{i-1}[C_{i}^c : C_{i-1}^c])$ of Eq 5 have the same form as Eq 3. This means that the $C_{i}^c$ to $C_{i-1}^c$ channels of data from each MHA layer’s input are not directly disturbed by any MHA of the front layer. The Eq 4 and Eq 5 enable the strongest strength IB in each layer to be passed to the MHA of the next layer with few distortions, thus enabling the efficient introduction of IB.

### 3.4. Network Architecture

#### 3.4.1 EIT

Based on the above analysis, we design a decreasing convolution structure to improve the efficiency of the IB introduction. The architecture of the proposed model is shown in Fig 5.

We propose two simple structures called EIT$^P$ (EIT for PaPr) and EIT$^T$ (EIT for TrEn) to form a complete decreasing structure. EIT$^P$ uses a convolution layer with a stride smaller than the kernel size, i.e., there are overlapping patches, which can improve the IB introduction efficiency of PaPr. However, it also means we will get redundant patches, introducing excess FLOPs. To solve this problem without seriously destroying the similarity of the adjacent patches, we filter out the redundant patches by a maximum pooling layer.

#### 3.4.2 EIT$^P$

Formally, given a 2D image $x \in \mathbb{R}^{H \times W \times C}$, we learn a function $f(\cdot)$ that maps $x_0$ into new embeddings $f(x) \in \mathbb{R}^{H' \times W' \times C'}$. $f(\cdot)$ is 2D convolution operation of kernel number $C'$, kernel size $k$, stride $s$ (In ViT, $s = k$, but in this work, $s < k$) and $p$ padding. The height and width of the new embedding $f(x)$ take the following values.

$$H' = \left\lfloor \frac{H + 2p - k + 1}{s} \right\rfloor, W' = \left\lfloor \frac{W + 2p - k + 1}{s} \right\rfloor$$  \hfill (6)$$

where $\left\lfloor \cdot \right\rfloor$ denotes rounding down. The height and width of $f(x)$ then reduced by a maximum pooling (maxpool) layer with kernel size and stride of $s_m$. By adjusting $s_m$,
we can reduce the redundant patches introduced by the convolution operation. $\text{maxpool}(f(x)) \in \mathbb{R}^{H_0 \times W_0 \times C_0}$, where $H_0 < H', W_0 < W', C_0 = C'$. Finally, $\mathbb{R}^{H_0 \times W_0 \times C_0}$ is transformed into $\mathbb{R}^{H_0 \times W_0 \times C_0}$ as the final output of EIT$^P$.

The above descriptions can be summarized in the following expression.

$$x_0 = \text{EIT}^P(x) = \text{Reshape1D}(\text{MaxPool}((\text{Conv}2D(x))))$$  \hfill (7)

### 3.4.3 EIT$^T$

The structure of the IB introduction in LSRA [22] contains one activation layer, one convolutional layer, and one fully connected layer. The difference is that EIT$^T$ contains only one layer of convolution. Because we believe that if we aim to introduce IB, we only need to have the convolutional layer. It does not matter much whether there are other types of layers (e.g., activation layers, fully connected layers) or how many convolutional layers there are. Alternatively, it does not cause a significant performance increase. We will discuss this issue in ablation studies.

Formally, given the normalized input $x_i \in \mathbb{R}^{(1+H,W) \times C_i}$ in the $i$-layer ("1" represents the added class embedding), different channel dimensions of data will be processed by MHA and EIT$^T$, respectively.

$$x_{i}^{\text{EIT}^T} \leftarrow \text{EIT}^T(x_i[1:\cdot, : C_{i}^{\text{EIT}^T}])$$ \hfill (8)

$$x_{i}^{\text{MHA}} \leftarrow \text{MHA}(x_i[1:\cdot, -C_{i}^{\text{MHA}}:])$$ \hfill (9)

where $C_{i}^{\text{EIT}^T}$ and $C_{i}^{\text{MHA}}$ are the number of channel dimensions processed by EIT$^T$ and MHA, respectively, satisfying $C_{i}^{\text{EIT}^T} + C_{i}^{\text{MHA}} = C_i$. The final output is the combination of the output of the MHA and the EIT$^T$.

$$x_i \leftarrow \text{Concat}(x_{i}^{\text{EIT}^T}, x_{i}^{\text{MHA}})$$  \hfill (10)

Since the convolution in EIT$^T$ handles two-dimension (2D) data, some dimensional transformations are involved before and after the convolution operation. Additionally, EIT$^T$ does not model the class embedding because it is challenging to perform 2D convolution operations if it is added. MHA, which is not repeated here, uses the same operation as ViT [5].

$$\text{EIT}^T(x_i) = \text{Concat}(x_i', x_i[0,:])$$ \hfill (11)

$$x_i' \leftarrow \text{Reshape1D}((\text{Conv}2D((\text{Reshape2D}(x_i[1:, :]))))$$ \hfill (12)

To ensure that $C_{i}^{\text{MHA}}$ is divisible by $h$ while $C_{i}^{\text{EIT}^T}$ decreases layer by layer, for a network with a total of $L$-layer encoders, the $C_{i}^{\text{EIT}^T}$ of layer $i$ is set to

$$C_{i}^{\text{EIT}^T} = C_i - [C_i / h \times r_i] \times h$$  \hfill (13)

where $\lceil \rceil$ denotes integer division, and $h$ is the number of heads in MHA, which generally requires $C_i$ to divide $h$. $r_i = i / L$, is the division ratio of $C_{i}^{\text{EIT}^T}$ to $C_{i}^{\text{MHA}}$. It is worth noting that $r_L = 1$, which will cause $C_{L}^{\text{EIT}^T}$ to take the value of 0. It is valid. Because MLP uses only the class embedding of the network’s last layer when classifying images and EIT$^T$ does not do anything to the class embedding. If there is an EIT$^T$ in the last layer, it also does not contribute to the result of the network.

### 4. Experiments

In this section, we evaluate the performance of EIT on small-scale datasets and verify the efficiency of the IB introduction of EIT.

#### 4.1. Setup

We use four popular small-scale datasets to evaluate the performance of EIT: Cifar10/100 [9], Fashion-Mnist [23],...
Table 2. Details of EIT model variants. "EIT3/4" indicates that the convolutional kernel size used in EIT$^P$ and EIT$^T$ is 3 (the stride is 1 by default), the kernel size and stride of the maxpool in EIT$^P$ is 4, and C is the number of channels (i.e., embedding dimension). The "Params" is for a 10-category classification task with an input image size of 32 * 32 and includes the trainable position embedding.

| Model               | C     | EIT$^P$ | EIT$^T$ | Layers | MLP Size | Heads | Heads | Params. |
|---------------------|-------|---------|---------|--------|----------|-------|-------|---------|
| EIT3/4-Mini         | 250   | $C@Conv:(3,3,1);$ | $C^{EIT^P-T}$ | 5      | 10       | 3.766M|
| EIT3/4-Tiny         | 330   | Maxpool:(4,4,4) | $@Conv:(3,3,1)$ | 8      | 4C       | 10.59M|
| EIT3/4-Base         | 400   |         |         | 10     | 16       | 19.54M|

Table 3. Details of model training. All the models are trained with a total batch size of 25 for 300 epochs. EIT belongs to ViTs.

| Method   | ViTs | ResNet | EfficientNet-b0,-b1,-b3 | EfficientNetV2-s,-m | MobileNetV2-(α=1.3,2.2) | MobileNetV3-large |
|----------|------|--------|-------------------------|---------------------|-------------------------|------------------|
| Optimizer| SGD  | Adam   | SGD                     | SGD                 | Adam                    | Adam             |
| Scheduler| Cosine | None | Cosine                 | Cosine              | None                    | None             |
| Ini Lr. Rate | 1e-3 | 5e-4 | 1e-3                   | 1e-3                | 1e-3                    | 5e-4             |
| End Lr. Rate | 1e-5 | None | 1e-5                   | None                | None                    | None             |
| Drop Ratio | 2e-1 | None | 1e-1                   | 1e-1                | 1e-1                    | None             |

and Tiny ImageNet-200 [15]. We conducted four major sets of experiments as follows. 1) The comparison with ViT-like methods (ViTs) (ViT [5], LSRA [22], CvT [21] and ViTC [24]). 2) The comparison with CNN-like methods (CNNs) (ResNet [7], EfficientNet [13], EfficientNetV2 [14], MobileNetV2 [11] and MobileNetV3 [8]). 3) The visualization of attention maps and attention distance for ViTs. 4) The ablation studies with Cifar10/100.

4.1.1 Model Variants

We design three sets of parameters as shown in Table 2 for the experiments. Next, we will use a simple notation to denote the model used.

4.1.2 Training

The details of training as shown in Table 3. In all experiments, we use only random horizontal flipping and normalization for data augmentation.

4.2. Comparison

4.2.1 Comparison with the ViTs

We discuss the performance of EIT based on EIT3/4-Mini. In addition to comparing ViT, we also compare how EIT introduces IB in both phases of ViT with that of CvT, LSRA and ViTC. The results are shown in Table 4. The results show that both structures of EIT exhibit more efficient IB introduction. On the four datasets, compared with ViT, EIT has the average improvement of 12.6% with fewer parameters and FLOPs. Compared with CvT, LSRA and ViTC, the average improvement of EIT are 6.4%, 7.3% and 10.7%, respectively.

4.2.2 Comparison with the CNNs

We compare the EIT with CNNs based on the proposed three model parameters in Table 5. The results show that EIT can achieve higher accuracy with fewer parameters than CNNs. In particular, comparing Model Idx 2.4 with Model Idx 2.13 of Table 5, we can see that EIT’s parameters are only 17.7% the scale of ResNet’s, while the FLOPs and accuracy are almost the same as those of ResNet, or even "better".

4.3. Visualization

To verify if the performance improvement of EIT is due to the improvement of header diversity, we computed the attention maps and attention distances of ViTs, as shown in Fig 4. It is clear that continuing to increase the head diversity of the network does improve the performance of ViT. Moreover, the efficient IB introduction can directly improve the head diversity of deep layers. Compared with other ViTs, EIT can introduce IB more efficiently based on Eq 4 and Eq 5 which results in better performance. Compared with CNNs, in which each layer has a constant attention distance, EIT has a variety of attention distances for each layer, which is why it is possible to achieve better performance with much fewer parameters. See more in Fig 5 and Fig 6. The increase of head diversity leads to a decrease in the attentional range of heads in each layer, which exhibits more focused attention on the average attention maps of each layer.

4.4. Ablation Study

On the Cifar10/100 dataset, we designed four ablation experiments based on EIT3/4-Mini to verify that: 1) EIT$^T$ works better than Parallel Convolution; 2) the presence or absence of convolutional layers in ELT$^T$ is essential; 3) compared with increasing and invariant structure, the de-
Table 4. Comparison with the ViTs. The structural parameters (C, Layers, MLP size and Heads) of ViTs are the same. In ViTs, all convolution operations are implemented without further parameter optimization. * We did not use the hierarchy in CvT, this is to ensure the fairness of the comparison of ViTs. The convolutional kernel size of CvT-P is 4, and the stride is 2. The value of \( n \) in \( \text{ViT}_C \) is 2, the convolutional kernel size is 4, and the stride is 2. Furthermore, we use a simple index (Idx) notation to denote the model compared in experiments.

| Model Idx | Method | Lead IB to PaPr Phase | Lead IB to TrEn Phase | FLOPs Pram. Num. | Cifar10 | Cifar100 | Fashion Mnvst | Tiny ImageNet | Avg. |
|-----------|--------|-----------------------|-----------------------|-----------------|----------|----------|--------------|---------------|------|
| 1.1       | ViT    | None                  | None                  | 0.515G 3.798M   | 0.682    | 0.413    | 0.888       | 0.246         | 0.557(+0.0%) |
| 1.2       | LSRA   | None                  | LTB                   | 0.487G 3.679M   | 0.778    | 0.477    | 0.910       | 0.276         | 0.610(+5.3%) |
| 1.3       | CvT    | None                  | None                  | 2.296G 3.846M   | 0.738    | 0.452    | 0.899       | 0.280         | 0.592(+3.5%) |
| 1.4       | CvT*   | None                  | CvT*                  | 1.838G 14.11M   | 0.712    | 0.414    | 0.909       | 0.233         | 0.567(+1.0%) |
| 1.5       | CvT    | CvT                   | CvT                   | 7.580G 14.16M   | 0.777    | 0.497    | 0.914       | 0.288         | 0.619(+6.2%) |
| 1.6       | ViT    | None                  | None                  | 0.553G 4.108M   | 0.700    | 0.414    | 0.909       | 0.233         | 0.567(+1.9%) |
| 1.7       | EIT3/4 | None                  | None                  | 0.527G 3.793M   | 0.746    | 0.479    | 0.911       | 0.283         | 0.605(+4.8%) |
| 1.8       | None   | EIT                   | None                  | 0.501G 3.771M   | 0.818    | 0.523    | 0.922       | 0.313         | 0.644(+8.7%) |
| 1.9       | (ours) | EIT                   | EIT                   | 0.514G 3.766M   | 0.855    | 0.605    | 0.926       | 0.346         | 0.683(+12.6%) |

Table 5. Comparison with the CNNs. The Model Idx 2.13 is the same as Model Idx 1.9 The "4/2" in "ResNet18-4/2" means the kernel size of \( \text{conv} \) in ResNet is \( 4 \times 4 \) and the stride is 2.

| Model Idx | Method | FLOPs Pram. Num. | Cifar10 | Cifar100 | Fashion Mnvst | Tiny ImageNet | Avg. |
|-----------|--------|-----------------|---------|----------|--------------|---------------|------|
| 2.1       | ResNet18-4/2  | 0.071G 11.19M   | 0.806   | 0.504    | 0.926       | 0.332         | 0.642 |
| 2.2       | ResNet18-3/1  | 0.221G 11.19M   | 0.841   | 0.544    | 0.934       | 0.380         | 0.675 |
| 2.3       | ResNet34-4/2  | 0.417G 21.31M   | 0.807   | 0.506    | 0.928       | 0.324         | 0.641 |
| 2.4       | ResNet34-3/1  | 0.585G 21.30M   | 0.846   | 0.549    | 0.936       | 0.388         | 0.680 |
| 2.5       | EfficientNet-b0 | 0.017G 4.062M   | 0.736   | 0.442    | 0.910       | 0.217         | 0.576 |
| 2.6       | EfficientNet-b1 | 0.026G 6.588M   | 0.730   | 0.414    | 0.916       | 0.228         | 0.572 |
| 2.7       | EfficientNet-b3 | 0.043G 10.80M   | 0.730   | 0.410    | 0.916       | 0.218         | 0.569 |
| 2.8       | EfficientNetV2-s | 0.124G 20.34M   | 0.769   | 0.424    | 0.925       | 0.226         | 0.586 |
| 2.9       | EfficientNetV2-m | 0.239G 53.16M   | 0.595   | 0.258    | 0.897       | 0.189         | 0.485 |
| 2.10      | MobileNetV2-(α=1.3) | 0.021G 3.783M   | 0.778   | 0.300    | 0.923       | 0.237         | 0.560 |
| 2.11      | MobileNetV2-(α=2.2) | 0.056G 10.61M   | 0.786   | 0.262    | 0.925       | 0.271         | 0.561 |
| 2.12      | MobileNetV3-large | 0.014G 4.239M   | 0.746   | 0.369    | 0.923       | 0.191         | 0.557 |
| 2.13      | EIT3/4-Mini    | 0.514G 3.766M   | 0.855   | 0.605    | 0.926       | 0.346         | 0.683 |
| 2.14      | EIT3/3-Mini    | 0.804G 3.775M   | 0.865   | 0.610    | 0.932       | 0.343         | 0.688 |
| 2.15      | EIT3/4-Tiny    | 1.415G 10.59M   | 0.859   | 0.618    | 0.928       | 0.354         | 0.690 |
| 2.16      | EIT3/3-Tiny    | 2.214G 10.60M   | 0.873   | 0.616    | 0.933       | 0.363         | 0.696 |
| 2.17      | EIT3/4-Base    | 2.593G 19.54M   | 0.863   | 0.614    | 0.929       | 0.356         | 0.691 |
| 2.18      | EIT3/3-Base    | 4.056G 19.63M   | 0.875   | 0.638    | 0.930       | 0.370         | 0.703 |

increasing structure is optimal; 4) EIT does not require position embedding.

4.4.1 Parallel Convolution

We investigated the performance of \( \text{EIT}^T \) (Decreasing Embedded Parallel Convolution) and Parallel Convolution (residual convolutional structure, i.e., each process all data and then sums them as the final output). The results are shown in Table 6. The accuracy of \( \text{EIT}^T \) is on average 2.2% higher than that of Parallel Convolution. Additionally, the number of parameters and FLOPs of \( \text{EIT}^T \) are both about 50% of its.

4.4.2 Complicating \( \text{EIT}^T \)

We assume that the role of the convolutional layer in \( \text{EIT}^T \) is only to introduce IB, so we only use one convolutional layer in \( \text{EIT}^T \). Next, we try to complicate \( \text{EIT}^T \) to see if it leads to an improvement in performance. For example,
Figure 4. Attention Distance and Attention Maps of ViTs. From top to bottom, these are the results for ViT [5], LSRA [22], CvT [21] and EIT, using Model Idx 1.1, 1.2, 1.5 and 1.9, respectively. The attention maps of each layer are obtained by averaging that of heads. The attention maps of each head are the average of all embeddings’. The attention distance is obtained by the same operation mentioned in Fig.2.
Figure 5. Attention Distance of EIT\(^P\), EIT\(^T\) and EIT. From left to right, these are the results for Model Idx 1.7, 1.8 and 1.9, respectively. The attention distance is obtained by the same operation mentioned in Fig.2. It can be found that the improve head diversity in the deeper layers of the network is mainly due to the effect of EIT\(^T\), which also proves the efficiency of the decreasing structure for IB introduction.

Figure 6. Attention Distance of EIT-Tiny and EIT-Base. From top to bottom and left to right, these are the results for Model Idx 2.15, 2.16, 2.17 and 2.18, respectively. The attention distance is obtained by the same operation mentioned in Fig.2. It can be seen that as the network deepens, the deeper layers of the EIT still possess a great head diversity, which justifies the Eq.4 and Eq.5.
Table 6. Ablations on Parallel Convolution.

| Model Idx | TrEn with structure | FLOPs | Pram. Num. | Cifar10 | Cifar100 | Average |
|-----------|---------------------|-------|------------|---------|---------|---------|
| 3.1(1.9)  | EIT $^T$            | 0.514G| 3.766M     | 0.855   | 0.605   | 0.730   |
| 3.2       | Parallel Convolution| 0.887G| 6.589M     | 0.841   | 0.574   | 0.708   |

we add multiple convolutional layers, activation layers, normalization layers, and fully connected layers. The results are shown in Table 7 showing that the one convolutional layer is more efficient.

Table 7. Ablations on Complicating EIT $^T$. The direction of data flow is all from top to down of the structure.

| Model Idx | Structure | FLOPs | Pram. Num. | Cifar10 | Cifar100 | Average |
|-----------|-----------|-------|------------|---------|---------|---------|
| 4.1(1.9)  | Conv      | 0.514G| 3.766M     | 0.855   | 0.605   | 0.730   |
| 4.2(1.7)  | None      | 0.527G| 3.793M     | 0.746   | 0.479   | 0.613   |
|           | Conv      | 0.687G| 5.116M     | 0.843   | 0.593   | 0.718   |
|           | Conv      | GELU  | 0.524G     | 3.841M  | 0.846   | 0.573   | 0.710   |
|           | Conv      | Fc    |            |         |         |         |
| 4.5       | BN        | 0.514G| 3.768M     | 0.851   | 0.577   | 0.714   |

4.4.3 Increasing and Invariant

We examine the performance of the decreasing structure in EIT $^T$, and the results are shown in Table 8. Compared with the Invariant and Increasing structures, the accuracy of Decreasing structure is 9% higher on average. The Fig.7 show that both increasing and invariant structures have slighter head diversity than decreasing structures because of the ineffective introduction of IB, which is consistent with the inference in Section 3.2-3.3. The last layer of the increasing and invariant structure have great head diversity because the last two layers are decreasing structures ($C^EIT_T$ for the three structure equals 0). This setting is because the last layer of convolution does not operate on class embedding.

4.4.4 Removing Position Embedding

Considering the introduction of convolutional operations in EIT, we investigated whether it still requires position embedding. The results are shown in Table 9 illustrate that the impact of removing position embedding on model performance is negligible. This is consistent with CvT [21]. The network without position embedding offers the possibility of simplified adaptation to more visual tasks without the need to redesign embedding. However, in the experiments of this paper, ViTs (including EIT) are added with trainable position embedding by default, which is to ensures the consistency of comparison among various methods.

Table 8. Ablations on Increasing and Invariant structure.

| Model Idx | Structure | Cifar10 | Cifar100 | Avg. |
|-----------|-----------|---------|----------|------|
| 5.1(1.9)  | Decreasing| 0.855   | 0.605    | 0.730|
| 5.2       | Increasing| 0.790   | 0.481    | 0.636|
| 5.3       | Invariant | 0.817   | 0.476    | 0.647|

Figure 7. Attention Distance of Decreasing, Increasing and Invariant structure. The attention distance is obtained by the same operation mentioned in Fig.2.

Table 9. Ablations on position embedding.

| Model Idx | Position Embedding | Cifar10 | Cifar100 | Avg. |
|-----------|--------------------|---------|----------|------|
| 6.1       | None               | 0.856   | 0.600    | 0.728|
| 6.2(1.9)  | Trainable          | 0.855   | 0.605    | 0.730|

5. Conclusion

In this work, we present a simple yet efficient network architecture that leads IB to ViT with fewer parameters and FLOPs, called EIT. EIT ensures the efficiency of introducing IB without destroying the unification of the network in CV and NLP. Extensive experiments are conducted to validate that the EIT has better performance than the previous ViTs (with IB) and CNNs. In addition, to the best of our knowledge, we find for the first time a strong correlation between the performance of the transformer and the diversity of head attention distance, which gives new ideas for further improving the performance of the transformer.
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