Integrally Pre-Trained Transformer Pyramid Networks

Yunjie Tian¹, Lingxi Xie², Zhaozhi Wang¹, Longhui Wei², Xiaopeng Zhang², Jianbin Jiao¹, Yaowei Wang³, Qi Tian², Qixiang Ye^{1,3}

¹University of Chinese Academy of Sciences

²Huawei Inc. ³Pengcheng Lab.

tianyunjie19@mails.ucas.ac.cn 198808xc@gmail.com wangzhaozhi22@mails.ucas.ac.cn weilonghui1@huawei.com zxphistory@gmail.com yaoweiwang@bit.edu.cn jiaojb@ucas.ac.cn tian.qi1@huawei.com qxye@ucas.ac.cn

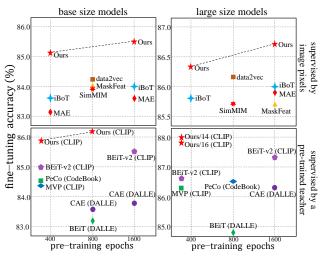
Abstract

In this paper, we present an integral pre-training framework based on masked image modeling (MIM). We advocate for pre-training the backbone and neck jointly so that the transfer gap between MIM and downstream recognition tasks is minimal. We make two technical contributions. First, we unify the reconstruction and recognition necks by inserting a feature pyramid into the pretraining stage. **Second**, we complement mask image modeling (MIM) with masked feature modeling (MFM) that offers multi-stage supervision to the feature pyramid. The pre-trained models, termed integrally pre-trained transformer pyramid networks (iTPNs), serve as powerful foundation models for visual recognition. In particular, the base/large-level iTPN achieves an 86.2%/87.8% top-1 accuracy on ImageNet-1K, a 53.2%/55.6% box AP on COCO object detection with 1× training schedule using Mask-RCNN, and a 54.7%/57.7% mIoU on ADE20K semantic segmentation using UPerHead - all these results set new records. Our work inspires the community to work on unifying upstream pre-training and downstream fine-tuning tasks. Code and the pre-trained models will be released at https://github.com/sunsmarterjie/iTPN.

1. Introduction

Recent years have witnessed two major progresses in visual recognition, namely, the vision transformer architecture [18] as network backbone and masked image modeling (MIM) [2, 25, 62] for visual pre-training. Combining these two techniques yields a generalized pipeline that achieves state-of-the-arts in a wide range of visual recognition tasks, including image classification, object detection, and instance/semantic segmentation.

One of the key issues of the above pipeline is the transfer



base-level models	IN-1K cls. acc.	det. AP	$MR, 1 \times)$ seg. AP	ADE20K (UP) seg. mIoU
iTPN-B prev. best	86.2 85.5 [45]	53.2 50.0 [10]	46.6 44.0 [10]	54.7 53.0 [45]
large-level models	IN-1K cls. acc.	det. AP	$MR, 1 \times)$ seg. AP	ADE20K (UP) seg. mIoU
iTPN-L prev. best	87.8 87.3 [45]	55.6 54.5 [10]	48.6 47.6 [10]	57.7 56.7 [45]

Figure 1. **Top**: on ImageNet-1K classification, iTPN shows significant advantages over prior methods, either only using pixel supervision (top) or leveraging knowledge from a pre-trained teacher (bottom, in the parentheses lies the name of teacher model). **Bottom**: iTPN surpasses previous best results in terms of recognition accuracy (%) on several important benchmarks. Legends – IN-1K: ImageNet-1K, MR: Mask R-CNN [27], UP: UPerHead [60].

gap between upstream pre-training and downstream finetuning. From this point of view, we argue that downstream visual recognition, especially fine-scaled recognition (*e.g.*, detection and segmentation), requires hierarchical visual features. However, most existing pre-training tasks (*e.g.*, BEiT [2] and MAE [25]) were built upon plain vision transformers. Even if hierarchical vision transformers have been used (*e.g.*, in SimMIM [62], ConvMAE [22], and Green-MIM [30]), the pre-training task only affects the backbone but leaves the neck (*e.g.*, a feature pyramid) un-trained. This brings extra risks to downstream fine-tuning as the optimization starts with a randomly initialized neck which is not guaranteed to cooperate with the pre-trained backbone.

In this paper, we present an integral pre-training framework to alleviate the risk. We establish the baseline with HiViT [67], an MIM-friendly hierarchical vision transformer, and equip it with a feature pyramid. To jointly optimize the backbone (HiViT) and neck (feature pyramid), we make two-fold technical contributions. **First**, we unify the upstream and downstream necks by inserting a feature pyramid into the pre-training stage (for reconstruction) and reusing the weights in the fine-tuning stage (for recognition). Second, to better pre-train the feature pyramid, we propose a new masked feature modeling (MFM) task that (i) computes intermediate targets by feeding the original image into a moving-averaged backbone, and (ii) uses the output of each pyramid stage to reconstruct the intermediate targets. MFM is complementary to MIM and improves the accuracy of both reconstruction and recognition. MFM can also be adapted to absorb knowledge from a pre-trained teacher (e.g., CLIP [47]) towards better performance.

The obtained models are named integrally pre-trained pyramid transformer networks (iTPNs). We evaluate them on standard visual recognition benchmarks. As highlighted in Figure 1, the iTPN series report the best known downstream recognition accuracy. On COCO and ADE20K, iTPN largely benefits from the pre-trained feature pyramid. For example, the base/large-level iTPN reports a 53.2%/55.6% box AP on COCO (1× schedule, Mask R-CNN) and a 54.7%/57.7% mIoU on ADE20K (UPer-Net), surpassing all existing methods by large margins. On ImageNet-1K, iTPN also shows significant advantages, implying that the backbone itself becomes stronger during the joint optimization with neck. For example, the base/largelevel iTPN reports an 86.2%/87.8% top-1 classification accuracy, beating the previous best record by 0.7%/0.5%, which is not small as it seems in such a fierce competition. In diagnostic experiments, we show that iTPN enjoys both (i) a lower reconstruction error in MIM pre-training and (ii) a faster convergence speed in downstream fine-tuning – this validates that shrinking the transfer gap benefits both upstream and downstream parts.

Overall, the key contribution of this paper lies in the integral pre-training framework that, beyond setting new stateof-the-arts, enlightens an important future research direction – unifying upstream pre-training and downstream finetuning to shrink the transfer gap between them.

2. Related Work

In the deep learning era [34], visual recognition algorithms are mostly built upon deep neural networks. There are two important network backbones in the past decade, namely, the **convolutional neural networks** [28,33,48] and the **vision transformers** [19,40,53,67]. This paper focuses on the vision transformers which were transplanted from the natural language processing field [52]. The core idea is to extract visual features by treating each image patch as a token and computing self-attentions among them.

The vanilla vision transformers appeared in a plain form [19,64,68] where, throughout the backbone, the number of tokens keeps a constant and the attention among these tokens are totally symmetric. To compensate the inductive priors in computer vision, the community designed hierarchical vision transformers [12, 40, 53, 59, 67] that allow the number of tokens to gradually decrease throughout the backbone, i.e., similar as in convolutional neural networks. Other design principles were also inherited, such as introducing convolution into the transformer architecture so that the relationship between neighborhood tokens is better formulated [12, 20, 36, 42, 53, 54], interacting between hybrid information [46], using window [16, 40, 67] or local [65] self-attentions to replace global self-attentions, adjusting the geometry for local-global interaction [63], decomposing self-attentions [51], and so on. It was shown that hierarchical vision transformers can offer high-quality, multi-level visual features that easily cooperate with a neck module (for feature aggregation, e.g., a feature pyramid [37]) and benefit downstream visual recognition tasks.

The continuous growth of vision data calls for visual pretraining, in particular, self-supervised learning that learns generic visual representations from unlabeled vision data. At the core of self-supervised learning lies a pretext task, i.e., an unsupervised learning objective that the model pursues. The community started with preliminary pretext tasks such as geometry-based tasks (e.g., determining the relative position between image patches [15, 43, 56] or the transformation applied to an image [23]), and generationbased tasks (e.g., recovering the removed contents [44] or attributes [66] of an image), but these methods suffer unsatisfying accuracy (i.e., trailed by fully-supervised pre-training significantly) when transferred to downstream recognition tasks. The situation was changed when new pretext tasks were introduced, in particular, contrastive learning [5, 6, 9, 24, 24, 26, 61] and masked image modeling (MIM) [2, 25, 62], where the latter is yet another type of generation-based learning objective.

This paper focuses on MIM, which takes the advantage of vision transformers which formulate each image

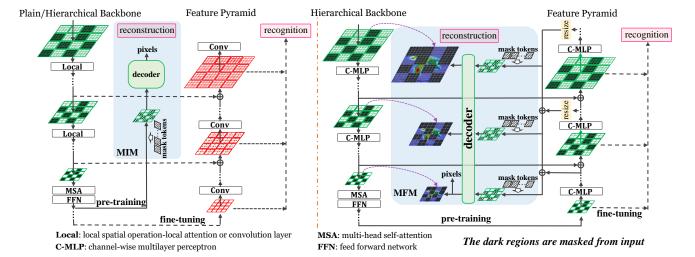


Figure 2. The comparison between a conventional pre-training (left) and the proposed integral pre-training framework (right). We use a feature pyramid as the unified **neck** module, and apply masked feature modeling for pre-training the feature pyramid. The green and red blocks indicate that the network weights are pre-trained and un-trained (*i.e.*, randomly initialized for fine-tuning), respectively.

patch into a token. Hence, the tokens can be arbitrarily masked (discarded from the input data) and the learning objective is to recover the masked contents at the pixel level [25, 62], the feature level [2, 55], or in the frequency space [39]. MIM has shown an important property named scalability, i.e., augmenting the amount of pretraining data (e.g., from ImageNet-1K to ImageNet-22K) and/or increasing the model size (e.g., from the base level to the large or huge level) can boost the downstream performance [10, 25], which aligns with the observations in language modeling [3, 14]. Researchers also tried to understand the working mechanism of MIM, such as separating representation learning from the pretext task [10], altering the input [21,50] or output [2,39,55] of the framework, increasing the difficulty of reconstruction [32,50], introducing supervision from other modalities [45, 57], etc.

Most existing MIM methods worked on the plain vision transformers, yet the hierarchical vision transformers have higher potentials in visual recognition. The first work which tried to bridge the gap was SimMIM [62], but the overall pre-training overhead was largely increased because the entire image (with dummy masked patches) were fed to the encoder. This issue was later alleviated by reforming the hierarchical vision transformers [30, 67] to fit MIM better. This paper inherits the design and goes one step further by integrating the neck (*e.g.*, a feature pyramid) into the pretraining phase, constructing the integrally pre-trained transformer pyramid network.

3. The Proposed Approach

3.1. Motivation: Integral Pre-Training

We first establish a notation system. The pre-training stage is built upon a dataset $\mathcal{D}^{\mathrm{pt}} = \{\mathbf{x}_n^{\mathrm{pt}}\}_{n=1}^N$, where N is the number of samples. Note that these samples are not equipped with labels. The fine-tuning phase involves another dataset $\mathcal{D}^{\mathrm{ft}} = \{\mathbf{x}_m^{\mathrm{ft}}, \mathbf{y}_m^{\mathrm{ft}}\}_{m=1}^M$, where M is the number of samples and $\mathbf{y}_m^{\mathrm{ft}}$ is the semantic label of $\mathbf{x}_m^{\mathrm{ft}}$. Let the target deep neural network be composed of backbone, neck, and head denoted as $f(\cdot; \boldsymbol{\theta}), g(\cdot; \boldsymbol{\phi}), h(\cdot; \boldsymbol{\psi})$, respectively, where $\boldsymbol{\theta}, \boldsymbol{\phi}, \boldsymbol{\psi}$ are learnable parameters and can be omitted for simplicity. $f(\cdot)$ directly takes \mathbf{x} as input, while $g(\cdot)$ and $h(\cdot)$ works on the outputs of $f(\cdot)$ and $h(\cdot)$ i.e., the entire function is $h(g(f(\mathbf{x}; \boldsymbol{\theta}); \boldsymbol{\phi}); \boldsymbol{\psi})$.

Throughout this paper, the pre-training task is masked image modeling (MIM) and the fine-tuning tasks can be image classification, object detection, and instance/semantic segmentation. Existing approaches assumed that they share the same **backbone**, but need different **necks** and **heads**. Mathematically, the pre-training and fine-tuning objectives are written as:

$$\min \mathbb{E}_{\mathcal{D}^{\text{pt}}} \| \mathbf{x}_n^{\text{pt}} - h^{\text{pt}}(g^{\text{pt}}(f(\mathbf{x}_n^{\text{pt}}; \boldsymbol{\theta}), \boldsymbol{\phi}^{\text{pt}}), \boldsymbol{\psi}^{\text{pt}}) \|,$$

$$\min \mathbb{E}_{\mathcal{D}^{\text{ft}}} \| \mathbf{y}_m^{\text{ft}} - h^{\text{ft}}(g^{\text{ft}}(f(\mathbf{x}_m^{\text{ft}}; \boldsymbol{\theta}), \boldsymbol{\phi}^{\text{ft}}), \boldsymbol{\psi}^{\text{ft}}) \|,$$
(1)

where parameters are not shared between $\phi^{\rm pt}$, $\phi^{\rm ft}$ and $\psi^{\rm pt}$, $\psi^{\rm ft}$. We argue that such a pipeline leads to a significant transfer gap between pre-training and fine-tuning, and thus brings two-fold drawbacks. **First**, the backbone parameters,

¹We follow the conventional definition that the neck is used for multistage feature aggregation (*e.g.*, a feature pyramid [37]) while the head is used for final prediction (*e.g.*, a linear classifier).

 $m{ heta}$, are not optimized towards being used for multi-level feature extraction. **Second**, the fine-tuning phase starts with optimizing a randomly initialized $m{\phi}^{\rm ft}$ and $m{\psi}^{\rm ft}$, which may slow down the training procedure and lead to unsatisfying recognition results. To alleviate the gap, we advocate for an integral framework that unifies $g^{\rm pt}(\cdot)$ and $g^{\rm ft}(\cdot)$, so that the pre-trained $m{\phi}^{\rm pt}$ is easily reused to be an initialization of $m{\phi}^{\rm ft}$, and thus only $m{\psi}^{\rm ft}$ is randomly initialized.

The overall framework is illustrated in Figure 2.

3.2. Unifying Reconstruction and Recognition

Let a hierarchical vision transformer contain S stages and each stage has several transformer blocks. Most often, the backbone (a.k.a encoder) gradually down-samples the input signal and produces S+1 feature maps:

$$f(\mathbf{x}; \boldsymbol{\theta}) = \mathbf{U}^0, \mathbf{U}^1, \dots, \mathbf{U}^S, \tag{2}$$

where \mathbf{U}^0 denotes the direct embedding of input, and a smaller superscript index indicates a stage closer to the input layer. Each feature map is composed of a set of **tokens** (feature vectors), *i.e.*, $\mathbf{U}^s = \{\mathbf{u}_1^s, \mathbf{u}_2^s, \dots, \mathbf{u}_{K^s}^s\}$, where K^s is the number of tokens in the s-th feature map.

We show that $g^{\mathrm{pt}}(\cdot)$ and $g^{\mathrm{ft}}(\cdot)$ can share the same architecture and parameters because both of them start with \mathbf{U}^S and gradually aggregate it with lower-level features. Thus, we write the neck part as follows:

$$\mathbf{V}^{S} = \mathbf{U}^{S},$$

$$\mathbf{V}^{s} = \mathbf{U}^{s} + q^{s}(\mathbf{V}^{s+1}; \boldsymbol{\phi}^{s}), \quad 1 \leq s < S,$$
(3)

where $g^s(\cdot)$ up-samples \mathbf{V}^{s+1} to fit the resolution of \mathbf{V}^s . Note that the learnable parameters, ϕ , are composed of a layer-wise parameter set, $\{\phi^s\}$. With these parameters being reused in fine-tuning, we largely shrink the transfer gap: the only modules that remain individual between pretraining and fine-tuning are the heads (e.g.), the decoder for MIM vs. the Mask R-CNN head for detection).

Before entering the next part that discusses the loss terms, we remind the readers that other differences exist between pre-training and fine-tuning, while they do not impact the overall design of network architectures.

- MIM samples a random mask \mathcal{M} and applies it to \mathbf{x} , *i.e.*, \mathbf{x} is replaced by $\mathbf{x} \odot \overline{\mathcal{M}}$. Consequently, all the backbone outputs, $\mathbf{U}^0, \dots, \mathbf{U}^S$, do not contain the tokens with indices in \mathcal{M} , and so are $\mathbf{V}^1, \dots, \mathbf{V}^S$. At the start of decoder, $\mathbf{V} = \sum_{s=1}^S \mathbf{V}^s$ is complemented by adding dummy tokens to the masked indices, and then fed into a decoder for image reconstruction.
- The downstream fine-tuning procedure makes use of specific outputs of decoder for different tasks. For image classification, \mathbf{V}^S is used. For detection and segmentation, all of $\mathbf{V}^1,\ldots,\mathbf{V}^S$ are used.

3.3. Masked Feature Modeling

We first inherit the reconstruction loss from MIM that minimizes $\|\mathbf{x}-h^{\mathrm{pt,0}}(\mathbf{V};\boldsymbol{\psi}^{\mathrm{pt,0}})\|$, where $h^{\mathrm{pt,0}}(\cdot)$ involves a few transformer blocks that reconstruct the original image from $\mathbf{V}=\sum_{s=1}^{S}\mathbf{V}^{s}$. To acquire the ability of capturing multi-stage features, we add a reconstruction head to each stage, termed $h^{\mathrm{pt,s}}(\cdot;\boldsymbol{\psi}^{\mathrm{pt,s}})$, and optimize the following multi-stage loss:

$$\mathcal{L} = \underbrace{\|\mathbf{x} - h^{\text{pt},0}(\mathbf{V})\|}_{\text{image reconstruction}} + \lambda \cdot \underbrace{\sum_{s=1}^{S} \|\mathbf{x}^{s} - h^{\text{pt},s}(\mathbf{V}^{s})\|}_{\text{feature reconstruction}}, \quad (4)$$

where \mathbf{x}^s is the expected output at the s-th decoder stage, and $\lambda=0.3$ is determined in a held-out validation set. Since the goal is to recover the masked features, we name the second term as the **masked feature modeling** (MFM) loss that complements the first term, the masked image modeling (MIM) loss. We illustrate MFM in Figure 2.

The remaining issue is to determine the intermediate reconstruction target, i.e., $\mathbf{x}^1,\ldots,\mathbf{x}^S$. We borrow the idea from knowledge distillation [29] that makes use of a teacher backbone $\hat{f}^{\text{back}}(\cdot)$ to generate the intermediate targets, i.e., $\hat{f}(\mathbf{x};\hat{\boldsymbol{\theta}}) = \mathbf{x}^1,\ldots,\mathbf{x}^S$. The teacher model is chosen to be the moving-averaged [49] encoder (in this case, no external knowledge is introduced) or another pre-trained model (e.g., CLIP [47], as used by [57,58], that was pre-trained on a large dataset of image-text pairs). In the former case, we only feed the masked patches ($\mathbf{x} \odot \mathcal{M}$, not the entire image) to the teacher model for acceleration. In the latter case, we follow BEiT [2] to feed the entire image to the pre-trained CLIP model.

As a side comment, the benefits brought by integral pretraining and MFM are individual and complementary – we shall reveal this point in the ablation (Table 6).

3.4. Technical Details

We build the system beyond HiViT [67], a recently proposed, hierarchical vision transformer. HiViT simplified the Swin transformers [40] by (i) replacing early-stage shifted-window attentions with channel-wise multi-layer perceptrons (C-MLPs) and (ii) removing the 7×7 stage so that global attentions are computed on the 14×14 stage. With these improvements, when applied to MIM, HiViT allows the masked tokens to be directly discarded from input (by contrast, with Swin as the backbone, SimMIM [62] required the entire image to be used as input), saving 30%–50% computational costs and leading to better performance.

Table 1 summarizes the configuration of iTPN. The computational complexity is comparable to that of ViT. We follow the convention to use 224×224 images during the pretraining. HiViT produces three stages (S=3) with spatial

Table 1. A comparison between ViT, Swin, HiViT, and the proposed iTPN in terms of network configuration. We use 224×224 input size to calculate the FLOPs. †: We add 4 Stage-3 blocks to HiViT-B to keep the FLOPs of iTPN-B comparable to ViT.

Model	ViT	Swin [40]	HiViT [67]	iTPN			
base-level models							
# stages	1	4	3	3			
# blocks	12	2+2+18+2	3+3+20	$3+3+24^{\dagger}$			
Params (M)	86	88	66	79			
FLOPs (G)	17.5	15.4	15.9	17.8			
large-level 1	nodel	s					
# stages	1	4	3	3			
# blocks	24	2+2+18+2	2+2+40	2+2+40			
Params (M)	307	197	288	288			
FLOPs (G)	61.3	34.5	61.2	61.2			

resolutions of 56×56 , 28×28 , and 14×14 , respectively. An S-stage feature pyramid is built upon the backbone. We replace all convolutions in the feature pyramid with C-MLPs to avoid leaking information from visible patches to invisible patches. As we shall see in ablation (Section 4.4), using C-MLP in the feature pyramid leads to consistent accuracy gain in various visual recognition tasks, and the improvement is complementary to that brought by MFM.

Regarding MFM, we investigate two choices of the teacher model. (i) The first option involves computing the exponential moving average (EMA) of the online target model with a coefficient of 0.996. We extract the supervision from the last layer of each stage, so that for any s, \mathbf{x}^s has the same spatial resolution as \mathbf{V}^s , and thus $h^s(\cdot)$ is a linear projection working on each token individually. (ii) The second option directly inherits a CLIP pre-trained model. Note that CLIP offers standard ViTs that do not produce multi-resolution feature maps. In this scenario, we unify the S MFM terms into one by down-sampling all the feature maps to the lowest spatial resolution (14×14) , adding them together, and comparing the sum to the last-layer output of the CLIP model.

4. Experiments

4.1. Settings and Implementation Details

We pre-train iTPN on the ImageNet-1K dataset [13], a subset of ImageNet that contains 1.28M training images of 1,000 classes. The class labels are not used during the pre-training stage. Each training image is pre-processed into 224×224 and partitioned into 14×14 patches sized 16×16 pixels. Following MAE [25], a random subset of 75% patches are masked from input, and the normalized pixels are preserved for reconstruction.

We use an AdamW optimizer [41] with an initial learn-

ing rate of 1.5×10^{-4} , a weight decay of 0.05, and batch size of $4{,}096$. The learning rate follows a cosine annealing schedule and the number of warm-up epochs is set to be 40. As mentioned above, the MFM supervision may come from the moving-averaged online model or a pretrained CLIP model. The numbers of pre-training epochs are 400 and $1{,}600$ in the former scenario, or 300 and 800 in the latter scenario². We train all these models using 64 NVIDIA Tesla-V100 GPUs. For the base-level models, one pixel-supervised epoch and one CLIP-supervised epoch take about 2.7 and 4.7 minutes, respectively. For the large-level models, the numbers are 4.2 and 12.0 minutes, respectively. That said, a 1600-epoch pixel-supervised pretraining of iTPN-base/large takes around 75/115 hours. We will provide more details in the appendix.

4.2. Image Classification

Fine-tuning We report results of ImageNet-1K classification. Following the convention, we insert a linear classifier on top of the last encoder block, and fine-tune the entire network. The number of epochs is 100 for base-level models and 50 for large-level models. We use the AdamW optimizer, with the initial learning rate being 5×10^{-4} and 1×10^{-3} for base-level and large-level models, respectively. The weight decay is 0.05 and the batch size is 1,024. The number of warm-up epochs is 5. The layer decay is set to be 0.55 and 0.50 for base-level and large-level models.

Results are summarized in Table 2. One can see that iTPN achieves higher accuracy than existing methods on all tracks, i.e., using base-level or large-level backbones, with or without external supervision (i.e., CLIP [47]). For example, using the base-level backbone, iTPN achieves an 85.1% accuracy with only 400 pre-training epochs, surpassing MAE [25] and HiViT [67] with 1,600 epochs. The accuracy of iTPN continues growing to 85.5% with 1,600 pre-training epochs, which is on par with BEiT-v2 [45] that distilled knowledge from CLIP-B [47] (1,600 epochs), yet iTPN reports an 86.2\% accuracy with the supervision of CLIP (800 epochs). Similar situations occur when we use the large-level backbone, where the advantage of iTPN is a bit smaller due to the higher baseline. The best practice appears when an iTPN-L/14 model (i.e., patch size is adjusted to 14×14) is supervised by a CLIP-L teacher – the classification accuracy, 88.0%, is the highest to date under fair comparisons.

Linear probing We then evaluate the pre-trained models using the linear probing test where the pre-trained backbone is frozen and only the newly initialized linear classifier is allowed to be fine-tuned. Therefore, compared to fine-tuning, linear probing raises a higher requirement

²By using CLIP as supervision, each pre-training epoch takes longer time but the pre-training converges faster. So, we adjust the number of pre-training epochs according to the computational budget.

Table 2. Top-1 classification accuracy (%) by fine-tuning the pretrained models on ImageNet-1K. We compare models of different levels and supervisions (e.g., with and without CLIP) separately.

Method at base-level	Arch.	Sup.	Eps.	Param. (M)	FT acc.
BEiT [2]	ViT-B	DALL-E	400	86	83.2
CAE [10]	ViT-B	DALL-E	800	86	83.6
PeCo [17]	ViT-B	codebook	300	86	84.5
MaskFeat [55]	ViT-B	HOG	800	86	84.0
SimMIM [62]	ViT-B	pixel	800	86	83.8
SimMIM [62]	Swin-B	pixel	800	88	84.0
data2vec [1]	ViT-B	pixel	800	86	84.2
ConvMAE [22]	ConViT-B	pixel	1600	88	85.0
MAE [25]	ViT-B	pixel	400	86	83.1
MAE [25]	ViT-B	pixel	1600	86	83.6
HiViT [67]	HiViT-B	pixel	800	66	84.2
iTPN (ours)	HiViT-B	pixel	400	79	85.1
iTPN (ours)	HiViT-B	pixel	1600	79	85.5
MVP [57]	ViT-B	CLIP-B	300	86	84.4
BEiT-v2 [45]	ViT-B	CLIP-B	1600	86	85.5
iTPN (ours)	HiViT-B	CLIP-B	300	79	85.9
iTPN (ours)	HiViT-B	CLIP-B	800	79	86.2
	A1.				
Method	A 1-	C	D	Param.	FT
Method at large-level	Arch.	Sup.	Eps.	Param. (M)	FT acc.
	Arch.	Sup.	Eps. 800		
at large-level				(M)	acc.
at large-level BEiT [2]	ViT-L	DALL-E	800	(M) 307	acc.
at large-level BEiT [2] PeCo [17]	ViT-L ViT-L	DALL-E codebook	800 800	(M) 307 307	85.2 86.5
at large-level BEiT [2] PeCo [17] MaskFeat [55]	ViT-L ViT-L ViT-L	DALL-E codebook HOG	800 800 300	(M) 307 307 307	85.2 86.5 84.4
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55]	ViT-L ViT-L ViT-L ViT-L	DALL-E codebook HOG HOG	800 800 300 1600	(M) 307 307 307 307	85.2 86.5 84.4 85.7
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62]	ViT-L ViT-L ViT-L ViT-L Swin-L	DALL-E codebook HOG HOG pixel	800 800 300 1600 800	(M) 307 307 307 307 197	85.2 86.5 84.4 85.7 85.4
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62] SimMIM [62] data2vec [1] CAE [10]	ViT-L ViT-L ViT-L ViT-L Swin-L Swin-H	DALL-E codebook HOG HOG pixel pixel	800 800 300 1600 800 800	(M) 307 307 307 307 197 658	85.2 86.5 84.4 85.7 85.4 85.7 86.2 86.3
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62] SimMIM [62] data2vec [1]	ViT-L ViT-L ViT-L ViT-L Swin-L Swin-H ViT-L	DALL-E codebook HOG HOG pixel pixel pixel	800 800 300 1600 800 800 800	(M) 307 307 307 307 197 658 307	85.2 86.5 84.4 85.7 85.4 85.7 86.2
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62] SimMIM [62] data2vec [1] CAE [10]	ViT-L ViT-L ViT-L ViT-L Swin-L Swin-H ViT-L ViT-L ViT-L ViT-L HiViT-L	DALL-E codebook HOG HOG pixel pixel pixel DALL-E pixel pixel	800 800 300 1600 800 800 800 1600 1600	(M) 307 307 307 307 197 658 307 307 307 288	85.2 86.5 84.4 85.7 85.4 85.7 86.2 86.3 85.9 86.1
at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62] SimMIM [62] data2vec [1] CAE [10] MAE [25]	ViT-L ViT-L ViT-L ViT-L Swin-L Swin-H ViT-L ViT-L ViT-L ViT-L	DALL-E codebook HOG HOG pixel pixel pixel DALL-E pixel	800 800 300 1600 800 800 800 1600	(M) 307 307 307 307 197 658 307 307 307	85.2 86.5 84.4 85.7 85.4 85.7 86.2 86.3 85.9
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at large-level BEiT [2] PeCo [17] MaskFeat [55] MaskFeat [55] SimMIM [62] SimMIM [62] data2vec [1] CAE [10] MAE [25] HiViT [67] iTPN (ours) iTPN (ours)	ViT-L ViT-L ViT-L Swin-L Swin-H ViT-L ViT-L HIVIT-L HIVIT-L HIVIT-L ViT-L HIVIT-L	DALL-E codebook HOG HOG pixel pixel pixel pixel pixel pixel pixel pixel cLIP-B	800 800 300 1600 800 800 1600 1600 400 1600 300	(M) 307 307 307 307 197 658 307 307 307 288 288 288 307	85.2 86.5 84.4 85.7 85.4 85.7 86.2 86.3 85.9 86.1 86.3
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for the pre-trained backbone. Following the convention, we train the models for 90 epochs using the LARS optimizer [31] with a batch size of 16,384 and a learning rate of 0.1. Similar to the situation of fine-tuning, iTPN outperforms all MIM-based methods in terms of classification accuracy. Specifically, the iTPN-B (pixel) model with 1,600 pre-training epochs reports a 71.6% accuracy, surpassing

Table 3. Top-1 linear probing (LIN) classification accuracy (%) by training the last classifier layer on ImageNet-1K. We compare models of different supervisions (*e.g.*, with and without CLIP) separately, using the base-level models.

Method at base-level	Arch.	Sup.	Eps.	Param. (M)	LIN acc.
BEiT [2]	ViT-B	DALL-E	400	86	49.4
MAE [25]	ViT-B	pixel	1600	86	67.8
SimMIM [62]	ViT-B	pixel	800	86	56.7
CAE [10]	ViT-B	DALL-E	1600	86	70.4
ConvMAE [22]	ConViT-B	pixel	1600	88	70.9
iTPN (ours)	HiViT-B	pixel	1600	79	71.6
MVP [57]	ViT-B	CLIP-B	300	88	75.4
iTPN (ours)	HiViT-B	CLIP-B	300	79	77.3

1,600-epoch MAE [25] by a significant margin of 3.8%, as well as 400-epoch BEiT, 800-epoch SimMIM, and 1,600-epoch CAE by 22.2%, 14.9%, and 1.2%, respectively. With CLIP supervision, iTPN with 300 epochs of pre-training reports a 77.3% accuracy, surpassing MVP [57] with the same setting by 1.9%.

Insights Note that image classification experiments do not involve transferring the pre-trained neck, *i.e.*, the feature pyramid. That said, iTPN achieves higher classification accuracy with the pre-trained backbone alone. This implies that (i) a joint optimization of backbone and neck leads to a stronger backbone, and hence, (ii) the derived backbone can be directly transferred for various vision tasks, extending iTPN to more application scenarios.

4.3. Detection and Segmentation

COCO: object detection & instance segmentation We follow the configuration provided by [10] to evaluate the pre-trained models on the COCO [38] dataset. We use Mask R-CNN [27] implemented by MMDetection [8]. We use the AdamW optimizer [41] with a weight decay of 0.05. The standard $1 \times (12 \text{ epochs})$ and $3 \times \text{ schedules}$ are applied, where the initial learning rate is 3×10^{-4} and it decays by a factor of 10 after 3/4 and 11/12 of fine-tuning epochs. The layer-wise decay rate is set to be 0.90. We also try a $3 \times \text{ Cascade Mask R-CNN [4]}$ towards higher accuracy. We apply multi-scale training and single-scale testing.

Results are summarized in Table 4. Compared to image classification, the advantages of iTPN become more significant because the pre-trained neck is reused, so that the fine-tuning stage only needs to initialize a task-specific head. For example, using a pixel-supervised base-level backbone, the $1\times$ Mask R-CNN produces 53.0% box AP, surpassing all other methods significantly (*e.g.*, +4.6% over MAE [25] and +3.0% over CAE [10]). Compared to HiViT that did not pre-train the feature pyramid, iTPN claims a

Table 4. Visual recognition results (%) on COCO (object detection and instance segmentation, AP) and ADE20K (semantic segmentation, mIoU). Mask R-CNN (abbr. MR, $1\times/3\times$) and Cascade Mask R-CNN (abbr. CMR, $1\times$) are used on COCO, and UPerHead with 512×512 input is used on ADE20K. For the base-level models, each cell of COCO results contains object detection (box) and instance segmentation (mask) APs. For the large-level models, the accuracy of $1\times$ Mask R-CNN surpasses all existing methods. †: ConvMAE used a different setting from all other methods – fine-tuning using ViTDet [35] for 25 epochs.

Method at base-level	Arch.	Sup.	Eps.	Param. (M)	MR, 1×	COCO MR, 3×	CMR, 3×	ADE20K UPerHead
MoCo-v3 [11]	ViT-B	pixel	300	86	45.5/40.5	_	_	47.3
BEiT [2]	ViT-B	DALL-E	400	86	42.1/37.8	_	_	47.1
DINO [7]	ViT-B	pixel	400	86	46.8/41.5	_	_	47.2
iBoT [69]	ViT-B	pixel	1600	86	_	_	51.2/44.2	50.0
CAE [10]	ViT-B	DALL-E	1600	86	50.0/44.0	-	_	50.2
SimMIM [62]	Swin-B	pixel	800	88	_	52.3/-	_	52.8
MAE [25]	ViT-B	pixel	1600	86	48.4/42.6	_	_	48.1
ConvMAE [22]	ConViT-B	pixel	1600	88	_	53.2/47.1 [†]	_	51.7
HiViT [25]	HiViT-B	pixel	1600	66	49.5/43.8	51.2/44.2	_	51.2
MVP [57]	ViT-B	CLIP-B	300	86	_	_	53.5/46.3	52.4
iTPN (ours)	HiViT-B	pixel	1600	79	53.0/46.5	54.0/47.4	56.0/48.5	53.5
iTPN (ours)	HiViT-B	CLIP-B	800	79	53.2/46.6	54.1/47.5	56.1/48.6	54.7
Method				Param.		COCO		ADE20K
at large -level	Arch.	Sup.	Eps.	(M)	object det.	instance seg.	schedule	UPerHead
MAE [25]	ViT-L	pixel	1600	307	54.0	47.1	MR, 1×	53.6
SimMIM [62]	Swin-L	pixel	800	197	53.8	_	MR, $3\times$	53.5
SimMIM [62]	SwinV2-H	pixel	800	658	54.4	_	MR, $3\times$	54.2
CAE [25]	ViT-L	pixel	1600	304	54.5	47.6	MR, $1\times$	54.7
iTPN (ours)	HiViT-L	pixel	1600	288	55.6	48.6	MR, $1\times$	56.1
iTPN (ours)	HiViT-L	CLIP-L	300	288	55.2	48.2	MR, $1 \times$	57.7

+1.7% gain in box AP. The $1\times$ Mask R-CNN results are even competitive among prior methods with a $3\times$ Mask R-CNN or a $3\times$ Cascade Mask R-CNN. With these stronger heads, iTPN reports stronger numbers, *e.g.*, the box/mask AP is 56.0%/48.5% using $3\times$ Cascade Mask R-CNN, setting a new record with base-level models. The advantages persist when either CLIP supervision is introduced or the large-level backbone is used. Later, we will show that the benefits indeed come from pre-training the feature pyramid and loading it for downstream fine-tuning.

ADE20K: semantic segmentation We follow BEiT [2] to build an UperHead [60] on top of the pre-trained backbone. We use the AdamW optimizer [41] and the learning rate is fixed as 3×10^{-5} . We fine-tune the model for a total of 160k iterations and the batch size is 16. The input resolution is 512×512 by default and we do not use multi-scale test. Results are summarized in Table 4. Again, iTPN reports the best accuracy in terms of mIoU. In particular, the pixel-supervised base/large-level models report 53.5%/56.1% mIoUs which surpass all the competitors substantially. Introducing CLIP supervision further improves both numbers by more than 1%, setting solid new records

Table 5. Ablations on whether the model is integrally pre-trained (iPT) and whether the feature pyramid is loaded for detection and segmentation. Fine-tuning on ImageNet-1K does not involve loading the pyramid. The numbers are in % for classification accuracy, box AP, and mIoU. The models are pre-trained for 400 epochs. For COCO, $1\times$ Mask R-CNN is used and box AP is reported.

iPT	loaded	ImageNet-1K	COCO	ADE20K
X	_	84.4	50.6	51.5
\checkmark	X	85.1	51.5	51.8
\checkmark	\checkmark	03.1	52.1	52.2

for both base-level and large-level models.

4.4. Analysis

Ablative studies Throughout this part, we use the 400-epoch pixel-supervised model for diagnosis. We first ablate the benefit of integral pre-training. As shown in Table 5, jointly optimizing the backbone and neck leads to higher recognition accuracy on all datasets including ImageNet-1K, COCO, and ADE20K. Beyond this point, loading the

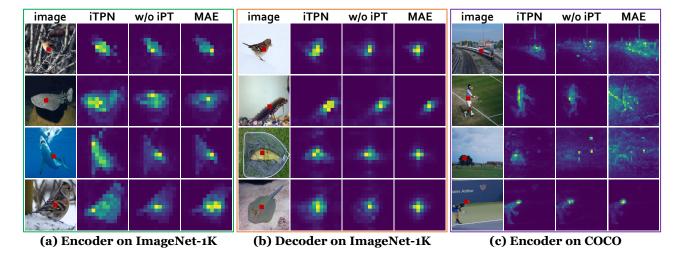


Figure 3. A comparison between the attention maps generated by iTPN, the variant without integral pre-training (w/o iPT), and the MIM baseline (MAE [25]). In each case, the red block indicates the query token, and the attention map between the query and other tokens at the corresponding transformer block is shown. We use 224×224 input images in (a), (b), and 512×512 images in (c).

Table 6. Ablations on C-MLP and MFM. The settings remain the same as in Table 5. The * sign indicates that convolution is used (instead of C-MLP) in the backbone and feature pyramid, which leads to worse recognition results.

C-MLP	MFM	ImageNet-1K	COCO	ADE20K
X *	Х	84.3	49.8	50.0
X *	\checkmark	84.6	50.8	50.7
\checkmark	X	84.9	51.8	51.8
\checkmark	\checkmark	85.1	52.1	52.2

pre-trained feature pyramid (neck) further improves the recognition accuracy on COCO and ADE20K. This validates that the backbone itself is strengthened by iTPN, and thus it can be transferred to downstream tasks independently of the neck.

Next, we investigate the technical details of integral

pre-training, in particular, using channel-wise multi-layer perceptron (C-MLP) in the feature pyramid and applying masked feature modeling (MFM) for multi-stage supervision. As shown in Table 6, both C-MLP and MFM contribute individually to recognition accuracy, meanwhile, integrating them yields even better recognition performance. **Visualization** In Figure 3, we visualize the attention maps generated by iTPN and baseline methods. (1) On the encoder, iTPN shows the advantage of detecting complete objects on ImageNet and concentrating on the chosen object on COCO. Such ability arises because iTPN forces the model to preserve richer visual features (multi-scale feature maps), which facilitates better recognition results in downstream. (2) On the decoder, iTPN can still realize the semantic relationship between tokens, resulting in better reconstruction results (Figure 4). We owe such benefits to the

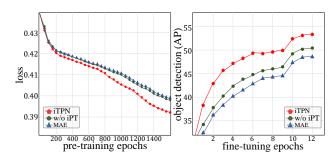


Figure 4. **Left**: the comparison of reconstruction loss values of different frameworks. **Right**: the comparison of convergence speed in terms of box AP on COCO when the pre-trained models are fine-tuned with Mask R-CNN for 12 epochs $(1 \times)$.

pre-trained neck that aggregates multi-stage visual features.

The benefits brought by more complete attentions can be quantified using two-fold experiments shown in Figure 4. (1) In the left part, we observe that iTPN achieves better reconstruction results (*i.e.*, lower reconstruction loss values). Note that simply using a hierarchical vision transformer (with multi-scale feature maps) does not improve reconstruction, implying that integral pre-training is the major contributor. (2) In the right part, we show that better depiction of objects helps downstream visual recognition tasks (*e.g.*, object detection) to converge faster and achieve a higher upper-bound – this aligns with the outstanding accuracy on COCO (see Section 4.3). Integrating these analysis, we conclude that iTPN successfully transfers the benefits from upstream pre-training (reconstruction) to downstream fine-tuning (recognition), completing the entire chain.

5. Conclusions and Future Remarks

In this paper, we present an integral framework for pre-training hierarchical vision transformers. The core contribution lies in a unified formulation that uses a feature pyramid for both reconstruction and recognition, so that the transfer gap between pre-training and fine-tuning is maximally reduced. Besides, a masked feature modeling (MFM) task is designed to complement masked image modeling (MIM) for a better optimization of the feature pyramid. The pre-trained iTPNs report superior recognition in a few popular visual recognition tasks. Our work clearly enlightens a future direction – designing a unified framework for upstream and downstream visual representation learning.

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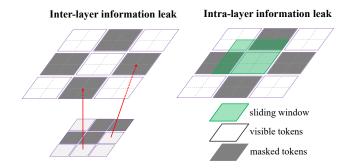


Figure 5. Information leak problems. **Left:** inter-layer information leak due from the normal tokens to masked tokens. **Right:** intra-layer information leak caused by spatial information interaction (such as convolutional operation) within the feature layer.

A. More Details on Experiments

We provide more details on experiments. For pixel-supervised models, the pre-training and fine-tuning details are provided in Tables 7 and 8, respectively. For CLIP-supervised models, the pre-training and fine-tuning details are provided in Tables 9 and 10, respectively. During pre-training using CLIP, we add an early-stage supervision at 3/4 of the third stage following BEiT-v2 [45].

Table 7. Hyperparameters for pre-training using image pixels as supervision on ImagetNet-1K.

Hyperparameters	base-scale	large-scale
Patch size	1	6
Hidden size	512	768
Layers	3-3-24	2-2-40
FFN hidden size	2048	3072
Attention heads	8	12
Attention head size	64	
Input resolution	224×224	
Training epochs	400/1600	
Optimizer	AdamW	
Base learning rate	1.5	e-4
Weight decay	0.05	
Optimizer momentum	$\beta_1, \beta_2 =$	0.9,0.95
Batch size	40	96
Learning rate schedule	cosine decay	
Warmup epochs	40	
Augmentation	RandomResizeCrop	
Absolute positional embedding	√	
Relative positional embedding		X

B. Handling Information Leak

When MIM-based methods are applied to pre-train iTPN, we encounter two kinds of information leak issues,

Table 8. Hyperparameters for fine-tuning using image pixels as supervision on ImagetNet-1K.

Hyperparameters	base-scale	large-scale	
Input resolution	224×224		
Training epochs	100	50	
Optimizer	Ada	mW	
Base learning rate	5e-4	1e-3	
Weight decay	0.0	05	
Layer decay	{.45,.5,.55}	{.5,.55,.6}	
optimizer momentum	$\beta_1, \beta_2 = 0$	0.9,0.999	
Batch size	1024		
Learning rate schedule	cosine decay		
Warmup epochs		5	
Label smoothing	0	.1	
Stoch. path	0.2	0.2	
Dropout		K	
Augmentation	RandAu	g (9,0.5)	
Mixup prob.	0	.8	
Cutmix prob.	1	.0	
Absolute positional embedding	•	/	
Relative positional embedding	•	<u> </u>	

namely, inter-layer and intra-layer information leak. Below, we elaborate them and describe the solutions.

The inter-layer information leak is related to the masking strategy used in this study, where the masking operation is applied across all the feature pyramid layers, *i.e.*, the hierarchical backbone and feature pyramid. As shown in Figure 5, independently and randomly masked tokens on different feature pyramid layers may cause the misalignment of masked tokens. Another kind of information leak is caused by the spatial overlapping of transformer pyramid layers, *i.e.*, the masked tokens in a pyramid layer can be easily reconstructed by that from adjacent layers, if those tokens are not masked. An intuitive solution is to spatially align the tokens to be masked across the feature pyramid. This simple operation achieves good performance as validated by experiments.

The intra-layer information leak is caused by the spatial information interaction across a feature map, as convolutions or window attentions involve integrating information from masked and unmasked neighboring pixels [22]. These local operations collect information of masked tokens so that the MIM pre-training target degenerates. To solve intra-layer information, we propose to use channel-wise MLP (C-MLP) to replace all convolution and window attention operations. As C-MLP is only used to connect tokens across transformer layers and does not use any intra-layer connections, it does not involve spatial information interactions. All the required spatial information interac-

Table 9. Hyperparameters for pre-training using CLIP models as supervision on ImagetNet-1K.

Hyperparameters	base-scale	large-scale	
Patch size	16	14/16	
Hidden size	512	768	
Layers	3-3-24	2-2-40	
FFN hidden size	2048	3072	
Attention heads	8	12	
Attention head size		64	
CLIP models	CLIP-B	CLIP-B/CLIP-L	
Input resolution	224×224		
Lay Training epochs	300/800	300	
Optimizer	AdamW		
Base learning rate		1.5e-3	
Minimal learning rate		1e-5	
Weight decay		0.05	
Optimizer momentum	β_1,β_2	= 0.9, 0.98	
Batch size		2048	
Gradient clipping		3.0	
Drop path	0.1	0.2	
Learning rate schedule	cos	ine decay	
Warmup epochs	10		
Augmentation	RandomResizeAndCrop		
Color jitter		0.4	
Absolute positional embedding	ng 🗸		
Relative positional embedding		✓	

tions are performed by the multi-head self-attention operations in deep transformer layers. This simple-yet-effective design not only solves intra-layer information leak, but also outperforms the window attention operations [40].

C. Generalizing to Plain Vision Transformers

In this part, we show that the proposed method also could be used on plain vision transformer (specifically ViT-B [19]). We up-sample the 4-th and 7-th layers from the backbone to $4\times$ and $2\times$ size features so that the hierarchical features are obtained to build the pyramid network. Other than that, all the rest modules of the architectures and settings are the same to iTPN. We summarize the results on Table 11. As shown, iTPN-ViT 400e model surpasses both MAE 1600e and 400e models by a large margin, which verifies the effectiveness of integrally pre-training method.

D. Computational Efficiency

We provide the comparison on throughputs between vanilla ViT models and the proposed iTPNs (*i.e.*, HiViT models). As shown in Table 12, iTPN models report the comparable inference speeds for both base and large-scale models.

Table 10. Hyperparameters for fine-tuning using CLIP models as supervision on ImagetNet-1K.

Hyperparameters	base-scale	large-scale	
Input resolution	224×224		
Training epochs	100	50	
Optimizer	Ada	mW	
Base learning rate	5e-4	1e-3	
Minimal learning rate	1e-6		
Layer decay	{.45,.5,.55}	{.5,.55,.6}	
optimizer momentum	$\beta_1, \beta_2 = 0$	0.9,0.999	
Batch size	10	24	
Learning rate schedule	cosine decay		
Warmup epochs	5		
Label smoothing	0	.1	
Stoch. depth	0.2	0.3	
Dropout		X	
Gradient clipping		X	
Weight decay	0.0	05	
Erasing prob.	0.:	25	
Augmentation	RandAug (9,0.5)		
Mixup prob.	0.8		
Cutmix prob.	1	.0	
Absolute positional embedding	·	(
Relative positional embedding	•	(

Table 11. Generalizing integral pre-training (iPT) to plain ViTs. All the results are reported with the same configurations by default. The numbers are in % for classification accuracy, box AP, and mIoU. The models are pre-trained for 400 epochs. For COCO, $1 \times$ Mask R-CNN is used and box AP is reported.

Method	epochs	ImageNet-1K	COCO	ADE20K
MAE	400	83.1	46.4	46.2
MAE	1600	83.6	48.4	48.1
iTPN	400	83.7	49.3	49.0

Table 12. Inference throughput (imgs/s) comparison with image size of 224×224 . We test all the results using the same settings and the GPU is a V100-32G machine. The models we used report comparable throughput compared to vanilla ViT models.

Models	Base	Large
ViT	278.3	91.4
HiViT	264.1	86.0

We then test the model complexity comparison in Table 13. We test the model complexity using the open analysis tool of MMdetection library [8] using the input size of 640×640 . One can see that iTPN-base reports

Table 13. A model complexity comparison between FPN [37] and iTPN on object detection using Mask-RCNN [27] framework. We show that iTPN uses comparable model complexity (Params and FLOPs) and enjoys better results ($1 \times$ training schedule here). We use the analysis tool provided by MMdetection [8] library to test the Params and FLOPs by using input size of 640×640 .

Method	Pyramid	Params (M)	FLOPs (G)	AP
MAE-B		115 103	389 397	48.4 53.0
MAE-L	pyramid network FPN [37]	338	756	54.0
	pyramid network		740	55.6

fewer model parameters (103M v.s. 115M) and comparable FLOPs (397G v.s. 389G) than ViT-base. For large-scale models, iTPN-large enjoys both of them: fewer model parameters (313M v.s. 338M) and lower FLOPs (740G v.s. 756G) compared to ViT-large.