ScaleNet: a convolutional network to extract multi-scale and fine-grained visual features

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ABSTRACT

Many convolutional neural networks have been proposed for image classification in recent years. Most tend to decrease the plane size of feature maps stage-by-stage, such that the feature maps generated within each stage show the same plane size. This concept governs the design of most classification networks. However, it can also lead to semantic deficiency of high-resolution feature maps as they are always placed in the shallow layers of a network. Here, we propose a novel network architecture, named ScaleNet, which consists of stacked convolution-deconvolution blocks and a multipath residual structure. Unlike most current networks, ScaleNet extracts image features by a cascaded deconstruction-reconstruction process. It can generate scale-variable feature maps within each block and stage, thereby realizing multiscale feature extraction at any depth of the network. Based on the CIFAR-10, CIFAR-100, and ImageNet datasets, ScaleNet demonstrated competitive classification performance compared to state-of-the-art ResNet. In addition, ScaleNet exhibited a powerful ability to capture strong semantic and fine-grained features on its high-resolution feature maps. The code is available at https://github.com/zhjpqq/scalenet.

INDEX TERMS

image classification, convolutional neural networks, resnet, deconvolution

I. INTRODUCTION

With the development of deep convolutional neural networks, image classification has achieved considerable progress in recent years. The early convolutional neural networks (CNNs) used for classification, such as NiN [1], VGG [2], Inception [3], [4], DSN [5], and HighwayNet [6], faced issues of vanishing/exploding gradients [7], [8]. Fortunately, with the development of ResNet [9] and DenseNet [10], these problems have been largely alleviated. ResNet [9] solved this problem by adding summation-skip-connections between different layers in each block, leading to the extension of many ResNet variants [11]–[24]. DenseNet [10] resolved the issue by constructing concatenation-skip-connections between a layer and all previous layers in a block, with various models developed subsequently [25]–[30]. Instead of the manual design method used in above networks, network architecture search (NAS) finds the optimal architecture by auto searching several key hyper-parameters of a baseline network, as seen in [23], [31]–[39].

However, to extract high-level semantic information, most classification networks tend to decrease feature size (i.e., plane size of feature maps, same below) and increase feature channels stage-by-stage until a 1D feature vector is generated. Thus, they sacrifice feature size to promote feature channels, resulting in feature dimension reduction. As a consequence, high-/low-resolution feature maps always occupy the shallow/deep layers of a network, respectively. On the other hand, the semantic information contained in feature maps usually increases in strength with network depth [40]. Therefore, high-resolution feature maps will always have weak semantic representation, whereas low-resolution feature maps will always have strong semantic representation. In other words, there exists an intrinsic trade-off between feature size and feature semantics for these CNNs. As such, the construction of a network that can eliminate this kind of compromise is important.

Inspired by the above consideration, we propose a novel network architecture, named ScaleNet. ScaleNet contains stacked convolution-deconvolution blocks and a multipath residual structure. Different from ResNet [9] and...
DenseNet [10], in which feature size remains unchanged within each stage. ScaleNet can generate scale-variable feature maps within each stage and block, as shown in Fig. 1. Based on this, ScaleNet can generate high-resolution feature maps in very deep layers, thus contributing to the ability to capture fine-grained visual features with strong semantic information. In addition, compared with the original residual structure used in ResNet [9], [12], our multipath residual structure has a stronger ability for both feature forward-propagation and gradient back-propagation, and can therefore improve parameter efficiency.

In summary, this paper makes the following contributions:

- Our network can generate scale-variable feature maps within each block and stage and can therefore realize multiscale feature extraction at any depth level of the network.
- Our network can learn fine-grained features with strong semantic representation for high-resolution feature maps.
- Our network has a multipath residual structure, which can further improve feature forward-propagation ability and gradient back-propagation ability of CNNs.

II. RELATED WORKS


Deconvolution has been well discussed in [47]–[49]. It can expand the plane size of an input tensor, and therefore often appears in vision tasks that need planar reconstruction. In these tasks, deconvolution layers are often attached to a classification backbone to reconstruct their feature maps, as seen in DeconvNet [50], DSSD [51], RRC [52], and HourglassNet [53]. In HourglassNet [53], each block is also built by a symmetrical convolution layer and deconvolution layer and the whole architecture is built by several stacked blocks. However, different from HourglassNet, our ScaleNet does not reduce the plane size of the feature maps in each block to 1 x 1 and therefore can always maintain high resolution of the feature maps.

III. NETWORK ARCHITECTURE

A. CONV-DECONV COUPLE

Our network architecture is shown in Fig. 2. The network contains three successive processing stages (i.e., stages 1, 2, and 3), each containing several stacked isomorphic blocks (surrounded by dotted boxes), with each block being a conv-deconv couple. There are two kinds of conv-deconv couples in Fig. 2, Conv-DeConv couple and Conv-Conv-DeConv-DeConv couple, which are named SingleCouple and DoubleCouple, respectively. SingleCouple is constructed by two stacked conv-unit and deconv-unit. DoubleCouple is constructed by two SingleCouple blocks, with one embedded in the other. These two couples can be used independently to build a network, and can also be mixed to build a network, as shown in Fig. 2. In addition, the lowercases (conv or deconv) refer to the convolution and deconvolution operations in general sense, while the uppercases (Conv or DeConv) refer to the convolution and deconvolution units in Fig. 2.
Fig. 2: Architecture of ScaleNet. ⊕ is summation sign.

a: Hyper-parameters
All Conv1 and Conv2 units in Fig. 2 have the same settings: i.e., kernel size, 3; stride, 2; padding, 1; dilation, 1; and no bias. All deconv-units in Fig. 2, including DeConv2, DeConv3, and DeConv4, have the same settings: i.e., kernel size, 3; stride, 2; padding, 1; dilation, 1; output padding, 1; and no bias. For each conv-unit and deconv-unit, BatchNorm and ReLU are attached to form BatchNorm-ReLU-Conv.

d: Naming rules
If a processing stage adopts DoubleCouple blocks, it is denoted with a postfix -D; if SingleCouple blocks are adopted, the stage is denoted with a postfix -S. For example, a network with three stages and 40 layers is denoted as ScaleNet40-DDSS, which means that its first stage contains five DoubleCouple blocks (-D5), second stage contains three DoubleCouple blocks (D3), and the third stage contains two SingleCouple blocks (S2). A depth of 40 indicates that the total number of convolution, deconvolution, and linear layers is 40.

B. MULTIPATH RESIDUAL STRUCTURE

The overall view of our multipath residual structure is shown in Fig. 2 and includes the green skip-connections within each conv-deconv block and the blue skip-connections across every two adjacent conv-deconv blocks. We call this residual structure a multipath residual structure. If we only retain the outermost green skip-connection within each block and remove all other skip-connections, it is the same as pre-active-ResNet [12], i.e., a single-path residual structure.

We denote the three successive DoubleCouple blocks in stage1 (see Fig. 2) as \(B_{i-1}, B_i, B_{i+1}\). For block \(B_i\), the weights and outputs of every unit (including Conv1, Conv2, DeConv3, and DeConv4) can be denoted as \((C_{i1}, C_{i2}, D_{i3}, D_{i4})\) and \((x_{i1}, x_{i2}, x_{i3}, x_{i4})\), respectively. The output of the last summing node in this block can be denoted as \(X_i\). We can then integrate BatchNorm and ReLU into the Conv/DeConv unit and obtain the following expressions to analyze the relationships among the three blocks.
According to the data flow in these three blocks \((B_{i-1}, B_i, B_{i+1})\), we have:

\[
X^i = x_4^i + X^{i-1} \quad (1)
\]

\[
X^{i+1} = x_4^{i+1} + X^i \quad (2)
\]

\[
= (A + D)X^i + Bx_3^i + Cx_2^i + X^i \quad \text{inside}, \quad A = D_i^{i+1}D_i^{i+1}C_{i+1}^{i+1}C_{i+1}^{i+1}
\]

\[
B = D_i^{i+1}D_i^{i+1}C_{i+1}^{i+1}C_{i+1}^{i+1}
\]

\[
C = D_i^{i+1}D_i^{i+1}C_{i+1}^{i+1}
\]

\[
D = D_i^{i+1}C_{i+1}^{i+1}
\]

Then we can calculate the residual of block \(B_{i+1}\):

\[
\text{Res}^{i+1}_{\text{single}} = X^{i+1} - X^i = AX^i = AX^{i-1} + Ax_4^i \quad (3)
\]

\[
\text{Res}^{i+1}_{\text{multi}} = X^{i+1} - X^i = AX^i + (DX^i + Bx_3^i + Cx_2^i)
\]

\[
= \text{Res}^{i+1}_{\text{single}} + DX^{i-1} + Dax_4^i + Bx_3^i + Cx_2^i \quad (4)
\]

where, \(\text{Res}^{i+1}_{\text{single}}\) refers to the residual of a single-path residual structure and \(\text{Res}^{i+1}_{\text{multi}}\) refers to the residual of a multipath residual structure. Comparing equations (3) and (4), if we disable \(D, B\) and \(C\) by changing the skip-connections from multipath to single-path, then \(\text{Res}^{i+1}_{\text{multi}}\) will equal \(\text{Res}^{i+1}_{\text{single}}\). Obviously, this demonstrates that the multipath residual structure is an extension of the original residual structure and can thereby spread the residual calculation of a block to more previous layers.

**IV. EXPERIMENTS AND RESULTS**

**A. DATASETS AND DATA AUGMENTATION**

The CIFAR-10 and CIFAR-100 datasets [54] both contain 50k training images and 10k test images with a size of 3x32x32. The CIFAR-10 dataset consists of 10 categories, whereas the CIFAR-100 dataset consists of 100 categories. As per [5], [9], [10], [12], the original training set of both CIFAR-10 and CIFAR-100 are split into 45k for training and 5k for validation. A standard data augmentation scheme, as used in [5], [9], [10], [12], is adopted for their training: i.e., four pixels are padded on each side and a 32 x 32 crop is randomly sampled from the padded image or its horizontal flip. Validation is carried out at the end of each training epoch. Testing is carried out on a single view of the original 32x32 image, and the final test error rate is reported on the 10k test sets.

The ImageNet2012 [55] dataset consists of 1.2 million training images and 50k validation images, containing 1000 categories and variable sizes. The test error rate is reported on its 50k validation images (denoted as ImageNet-1k val). For training on ImageNet, a standard data augmentation scheme provided by PyTorch is adopted, in which a random-sized crop (0.08 ~ 1.0 of original size) and random aspect ratio (3/4 ~ 4/3 of original aspect ratio) is first made on an image or its horizontal flip, after which the crop is resized to 224x224. The color augmentation and normalization used in other studies [9], [10], [12], [56] are also adopted. For testing on ImageNet, we adopt 1-crop testing and 10-crop testing, in which the crop size is 224x224 on a 256x256 image and 320x320 on a 350x350 image. In both testing situations, the crops are normalized by the mean and variance of ImageNet.

**B. LEARNING SCHEDULE**

Both CIFAR-10 and CIFAR-100 are trained on 2x NVIDIA TitanX GPUs with a batch size of 128. The optimizer is a stochastic gradient descent (SGD) with a learning rate starting from 0.1 and divided by 10 at the 240th and 270th epochs, respectively, with 300 training epochs in total. The weight decay and momentum are 0.0001 and 0.9, respectively. ImageNet is trained on 4x NVIDIA 1080Ti GPUs with a batch size of 256, and the learning schedule is the same as that in [9], [10], [12], [56]. The optimizer is SGD with a learning rate starting from 0.1 and divided by 10 at every 30 epochs, with a total of 100 training epochs. The weight decay and momentum are 0.0001 and 0.9, respectively. The weights are initialized as in [57] and BatchNorm as in [58]. For all our networks, the loss functions are cross entropy loss and no dropout is adopted.

**C. RESULTS ON CIFAR-10 AND CIFAR-100**

Several ScaleNets with different parameter scales are designed for CIFAR-10 and CIFAR-100. The experimental results are shown in Table 1, together with current results from several other papers, especially ResNets and its variants. Our best results are marked in bold and the best overall results are marked in blue.

1) Accuracy

For the CIFAR-10 dataset, our deep ScaleNet with a distinct parameter reduction of 30% (1.2M parameters and 222 layers) achieves better performance (5.39%) than that of ResNet (6.41%, 1.7M), SD-ResNet (5.43%, 1.7M), pre-ResNet (5.46%, 1.7M), ELU-ResNet (5.62%, 1.7M), and PELU-ResNet (5.37%, 1.7M). Our deep ScaleNet with 1.7M parameters and 444 layers achieves a far better error rate (4.96%) than that of ResNet (6.41%, 1.7M), SD-ResNet (5.43%, 1.7M), pre-ResNet (5.46%, 1.7M), RIR (5.01%, 10.3M), ELU-ResNet (5.62%, 1.7M), PELU-ResNet (5.37%, 1.7M), FitResNet (5.39%, 2.5M), and Attention-ResNet (4.99%, 1.9M). Meanwhile, our wide ScaleNet with 1.7M parameters and 98 layers also shows an approximate error rate of 5.06%. Furthermore, the deep ScaleNet with 10M parameters achieves better performance (4.46%, 1432L) than that of SD-ResNet (4.91%, 1202L, 10M), Pre-ResNet (4.62%, 1001L, 10M), Wide ResNet (4.81%, 16L, 11M), RIR (5.01%, 18L), and CRMN (4.65%, 40M+).

For the CIFAR-100 dataset, our deep ScaleNet with a substantial parameter reduction of 30% (1.2M parameters) performs better (24.13%) than ResNet (27.22%, 1.7M), SD-ResNet (24.58%, 1.7M), pre-ResNet (24.33%, 1.7M), ELU-ResNet (26.55%, 1.7M), PELU-ResNet (25.04%, 1.7M), and FitResNet (27.66%, 2.5M). In addition, the wide ScaleNet
with 1.7M parameters achieves a much lower error rate (23.24%) than the above models. Our wide ScaleNet with 10M parameters also attains a lower error rate (21.97%) than that of Wide ResNet (22.07%, 11M) and RiR (22.90%, 10M). Thus, our results from CIFAR-10 and CIFAR-100 confirm the marked advantage of ScaleNet over ResNet [9], DenseNet-BC [10], Stochastic-Depth [11], Wide ResNet [44], PELU-ResNet [43], and PReLU-ResNet [60].

The training and validation curves of a very deep ScaleNet [59] with dropout/drop-path and pre-activation [59] in the third stage are shown in Fig.3. It contains 200 DoubleCouple blocks, indicating that the feature maps in this stage will continuously vary 272 times in [32x32, 16x16, 8x8, 16x16, 32x32]. Its second stage contains 50 SingleCouple blocks and the feature maps in this stage will vary 50 times in [8x8, 4x4, 8x8]. From the train-loss and val-loss curves in Fig.3, we can clearly see slight over-fitting in the training stage at the iteration of 64k. However, the val-prec curve still maintains a slow rise and does not worsen with the rise of val-loss, suggesting that over-fitting is within an acceptable range. Though it is an extremely deep network, even deeper than ResNet (1202L, 10.2M, 7.93%, in Table.1) by 1.6x, serious over-fitting does not exist, and it achieves a much lower error rate of 4.53%.

### TABLE 1: Classification performance of ScaleNets on CIFAR-10 and CIFAR-100. \textit{Params} refers to the parameter scales of networks, with a unit of M (1M means 10^6).

<table>
<thead>
<tr>
<th>Model</th>
<th>Depth</th>
<th>Params (M)</th>
<th>CIFAR-10+</th>
<th>CIFAR-100+</th>
</tr>
</thead>
<tbody>
<tr>
<td>FractalNet [59]</td>
<td>21</td>
<td>38.6</td>
<td>5.22</td>
<td>23.30</td>
</tr>
<tr>
<td>With dropout/drop-path</td>
<td>21</td>
<td>38.6</td>
<td>4.60</td>
<td>23.73</td>
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<tr>
<td>ResNet [9]</td>
<td>110</td>
<td>1.7</td>
<td>6.61</td>
<td></td>
</tr>
<tr>
<td>Reported by [11]</td>
<td>110</td>
<td>1.7</td>
<td>6.41</td>
<td>27.22</td>
</tr>
<tr>
<td>1202</td>
<td>19.4</td>
<td>7.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ResNet:</td>
<td>110</td>
<td>1.7</td>
<td>5.23</td>
<td>24.58</td>
</tr>
<tr>
<td>ELU-ResNet [42]</td>
<td>110</td>
<td>1.7</td>
<td>5.62</td>
<td>26.35</td>
</tr>
<tr>
<td>PELU-ResNet [43]</td>
<td>110</td>
<td>1.7</td>
<td>5.37</td>
<td>25.04</td>
</tr>
<tr>
<td>Wide ResNet [44]</td>
<td>18</td>
<td>11.0</td>
<td>4.81</td>
<td>22.97</td>
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<td>28</td>
<td>36.5</td>
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<td>20.50</td>
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<td>1001</td>
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<td>Attention-ResNet [16]</td>
<td>92</td>
<td>1.9</td>
<td>4.99</td>
<td>21.71</td>
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<td>236</td>
<td>5.1</td>
<td>4.14</td>
<td></td>
<td>21.16</td>
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<tr>
<td>452</td>
<td>8.6</td>
<td>3.90</td>
<td></td>
<td>20.45</td>
</tr>
<tr>
<td>FitResNet [60]</td>
<td>-</td>
<td>2.5M</td>
<td>5.84</td>
<td>27.66</td>
</tr>
<tr>
<td>ResNet-in-ResNet [14]</td>
<td>18</td>
<td>10.3</td>
<td>5.01</td>
<td>22.90</td>
</tr>
<tr>
<td>CRMN [75]</td>
<td>28</td>
<td>40.1</td>
<td>4.65</td>
<td>20.35</td>
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<tr>
<td>WRN40</td>
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<td>4.09</td>
<td>20.11</td>
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<td>WRN58</td>
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<td>1202</td>
<td>19.4</td>
<td>4.49</td>
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<tr>
<td>DenseNet-BC [10]</td>
<td>100</td>
<td>0.8</td>
<td>4.51</td>
<td>22.37</td>
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<tr>
<td>100</td>
<td>7.0</td>
<td>4.10</td>
<td>20.20</td>
<td></td>
</tr>
<tr>
<td>250</td>
<td>15.0</td>
<td>3.62</td>
<td>17.60</td>
<td></td>
</tr>
</tbody>
</table>

| Wide ScaleNet:         |      |            |           |            |
| ScaleNet-D             | 32    | 1.0        | 5.50      | 25.18      |
| ScaleNet-DDS           | 98    | 1.7        | 5.06      | 23.24      |
| ScaleNet-DDS           | 90    | 10.0       | 5.10      | 21.97      |
| ScaleNet-DDS           | 157   | 15.0       | 4.29      | 21.33      |

| Deep ScaleNet:         |      |            |           |            |
| ScaleNet-DDS           | 632   | 1.0        | 5.48      | 28.08      |
| ScaleNet-DDS           | 222   | 1.2        | 5.39      | 24.13      |
| ScaleNet-DDS           | 444   | 1.7        | 4.96      | 25.25      |
| ScaleNet-DDS           | 1432  | 10.0       | 4.46      | 23.37      |
| ScaleNet-DDS           | 2000  | 15.0       | 4.53      |            |

**D. RESULTS ON IMAGENET**

We compared ScaleNet with ResNet [9] and DenseNet [10] on ImageNet [55] classification tasks. The ResNets and DenseNets are the pre-trained models provided by PyTorch. Table.2 shows the evaluation results of the ScaleNets on ImageNet-1k val based on 320x320 crops from 350x350 images. Fig.4 shows the top-1 validation error rates on ImageNet-1k val as a function of learned parameters and floating-point operations (FLOPs), as well as their inference time and inference memory on a single TitanX GPU. Evaluation is carried out on 224x224 crops from 256x256 images.

As seen in Fig.4 (a, b), our ScaleNets significantly outperform the ResNets under relatively small parameter scales; however, the DenseNets perform better than the ResNets and ScaleNets in regard to parameter efficiency and FLOPs. For any classification network, inference time and memory are two irreplaceable aspects reflecting computation costs. Both parameter scales and FLOPs are reflected on these two variables. Thus, we conducted an experiment to comprehensively compare the inference time and memory of different networks, with results shown in Fig.4 (c). As seen in this figure, the ScaleNets perform similarly to ResNets, but outperform DenseNets in regard to both inference time and memory. Even the largest ScaleNet-58(30M) is better than the smallest DenseNet-121(8M) for both inference time and memory. Thus, under the trade-off of efficiency and accuracy, ScaleNet performance is competitive against these state-of-
TABLE 2: 1-crop and 10-crop validation on ImageNet-1k val.

<table>
<thead>
<tr>
<th>Model</th>
<th>Depth</th>
<th>Params(M)</th>
<th>FLOPs(G)</th>
<th>Top-1 Error (1-crop)</th>
<th>Top-1 Error (10-crops)</th>
<th>Top-5 Error (1-crop)</th>
<th>Top-5 Error (10-crops)</th>
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<tbody>
<tr>
<td>ScaleNet-D_{25}</td>
<td>103</td>
<td>5.1</td>
<td>4.8</td>
<td>27.10</td>
<td>26.14</td>
<td>9.15</td>
<td>8.42</td>
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<td>ScaleNet-D_{4*}</td>
<td>68</td>
<td>10.1</td>
<td>4.8</td>
<td>25.57</td>
<td>24.66</td>
<td>7.71</td>
<td>7.04</td>
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<tr>
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<td>44</td>
<td>9.4</td>
<td>2.4</td>
<td>26.98</td>
<td>25.80</td>
<td>8.58</td>
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<td>38</td>
<td>15.0</td>
<td>3.0</td>
<td>25.32</td>
<td>24.20</td>
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<td>23.46</td>
<td>22.30</td>
<td>6.77</td>
<td>6.12</td>
</tr>
</tbody>
</table>

FIGURE 4: Top-1 validation error rate as a function of learned parameters (a) and FLOPs (b). Comparison of inference memory and inference time (c).

The experimental method of Fig.4(c). We evaluate networks with a fake input image (random tensor with a shape of 1x3x224x224) on a single NVIDIA TitanX GPU for 5000 cycles and count the running time and GPU memory usage. Because the input is a very small tensor and can be initialized in GPU memory, there is no time or memory cost for data loading and preprocessing. Therefore, the running time and GPU memory used are only related to the network inference processing. The running time is counted from the start to the end of 5000 cycles. The GPU memory is read from the NVIDIA-SMI board, which can be opened by a command line ‘watch -n 1 nvidia-smi’ on Linux OS. After a very short start-up stage (< 8s), the Memory-Usage and GPU-Util shown on the NVIDIA-SMI board reach their respective stable values, and thereafter remain unchanged to the end of 5000 cycles. Thus, the GPU-Util values are always between 96%–98% for all networks compared, which proves that the GPU always runs at full speed. Under this state, we record the Memory-Usage value shown on NVIDIA-SMI board as the inference memory of a network. In addition, we record the average running time of 5000 cycles as the inference time of a network. Lastly, to eliminate device impact, inference time is normalized to (0, 1] by dividing the inference time of each network by the maximum inference time of all networks. Inference memory and precision are similarly normalized to (0, 1]. The final results in Fig.4 (c) are relative values of inference time, memory, and precision based on all networks, thus providing more reasonable comparison between efficiency and accuracy.

E. ABLATION STUDIES

1) Conv-deconv block

We use DoubleCouple blocks to build two one-stage ScaleNets for CIFAR-10, i.e., ScaleNet32-D_{7}(1.0M) and ScaleNet44-D_{10}(2.0M). The feature maps generated by ScaleNet44-D_{10} are shown in Fig.1. This figure demonstrates that ScaleNet can completely remove the constraints between feature size and feature semantics. The high-resolution feature maps can be found at any depth level of this network. Table.3 shows the classification results, which demonstrate that ScaleNet performs much better than ResNet and pre-active-ResNet. In particular, the numbers of DeConv-units and Conv-units are almost equal in the ScaleNets, thus demonstrating the effectiveness of feature extraction based on a strong deconstruction-reconstruction process.

TABLE 3: Classification performance of two one-stage ScaleNets on CIFAR-10.

<table>
<thead>
<tr>
<th>Model</th>
<th>Conv:DeConv</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet110 (1.7M)</td>
<td>110: 0</td>
<td>6.41%</td>
</tr>
<tr>
<td>pre-active-ResNet164 (1.7M)</td>
<td>164: 0</td>
<td>5.46%</td>
</tr>
<tr>
<td>ScaleNet32 (1.0M)</td>
<td>17: 14</td>
<td>5.50%</td>
</tr>
<tr>
<td>ScaleNet44 (2.0M)</td>
<td>23: 20</td>
<td>5.25%</td>
</tr>
</tbody>
</table>

2) Comparison with pooling and interpolation

In addition to the convolution layers of stride 2 (denoted as A) and deconvolution layers of stride 2 (denoted as B) used...
in Fig. 2, other methods can be used to resize feature maps. For example, a convolution layer of stride 1 followed by a pooling layer of stride 2 (denoted as C) can halve the plane size of feature maps; whereas an interpolation layer of scale 2 followed by a convolution layer of stride 1 (denoted as D) can double the plane size of feature maps. In C and D, the pooling and interpolation layers are used to adjust the plane size of feature maps, whereas the convolution layers of stride 1 are used to adjust the channels of feature maps. Based on the design of C and D, ScaleNet can also ensure that both input and output display the same resolutions and channels within a block.

We compare these different up-/down-sampling methods (A, B, C, D) below. We use several standard ScaleNets with the design of A+B (denoted as ScaleNet(A+B)) as baseline networks, then first replace B with D to form ScaleNet(A+D), and then replace A with C to form ScaleNet(C+D). Table 4 shows the experimental results on CIFAR-10 and CIFAR-100, in which Time refers to the average inference time calculated on a single TitanX GPU with a total of 100 cycles. Fig. 5 shows the validation curves of ScaleNet-D30 with different up-/down-sampling methods on CIFAR-10.

Comparing the two columns A+B and A+D in Table 4, we find that the two up-sampling methods (B and D) have the same parameters and FLOPs. The two ScaleNets on CIFAR-10 (ScaleNet-D30, ScaleNet-D30S10) show almost equal error rates (5.5% vs 5.7% vs 5.9% vs 5.8%). Furthermore, from the two ScaleNets on CIFAR-100 (ScaleNet-D30, ScaleNet-D30S10, ScaleNet-D30S12), A+B and A+D also exhibit similar performances (22.2% vs 23.1% vs 24.8% vs 24.3%). This suggests that up-sampling method B is almost equal to D. Comparing the columns A+B and C+D, as well as A+D and C+D in Table 4, the models under C+D show lower error rates but higher FLOPs and inference time than the models under A+D for both CIFAR-10 and CIFAR-100. Of note, compared with the slight decrease in error rates, computation complexity (FLOPs) and inference time increase by more than 50% and 40% respectively, thus suggesting that down-sampling method C is better than A, but exhibits a serious side-effect of fast-increasing FLOPs and inference time. In summary, this comparative experiment reveals that the conv-deconv blocks used in our ScaleNet demonstrate a better trade-off between accuracy and efficiency.

3) Multi-path residual structure

Here, we use ScaleNet32-D7 and ScaleNet98-D20S5, without any skip-connections, as two backbones, and then add two kinds of skip-connections to them, i.e., ‘SinglePath’ and ‘MultiPath’. SinglePath method means only one inner skip-connection is built within each block. It is typically used in ResNet and pre-ResNet and is shown as the outer-most green line within each block in Fig. 2. Our MultiPath method includes all skip-connections shown in Fig. 2. As skip-connections do not add new parameters to a backbone, the resulting networks retain the same parameter scales. As shown in Table 5, MultiPath method is far superior to the SinglePath method. This is in accordance with the theoretical proof in Section III-B, which convincingly suggests that a multipath residual structure can further strengthen feature forward propagation and gradient back-propagation and can therefore significantly promote the parameter efficiency of networks.

F. FEATURE SEMANTICS ANALYSIS

Here, we use three pre-trained one-stage ScaleNets (as in Fig. 1) on CIFAR-10, CIFAR-100, and ImageNet as backbones, and then attach auxiliary classifiers to the smallest feature maps generated by each of their DoubleCouple blocks. All these feature maps possess the same dimensions, and thus the attached auxiliary classifiers have the same structure. We then train the auxiliary classifiers under the same initialization state and training schedule. Obviously, because the feature maps are frozen, the training of the auxiliary classifiers is independent of each other. As seen in Fig. 6, classification precision gradually increases with network depth. The auxiliary classifiers have the same potential learning ability but perform very differently according to the feature maps to which they are attached. Obviously, this reveals that the semantic information contained in the feature maps gradually increases with network depth. This further demonstrates the effectiveness of feature extraction based on a cascaded deconstruction-reconstruction process.

G. FEATURE-MAPS ANALYSIS

Here, to analyze the multiscale ability of ScaleNet, we visualize class activation maps (CAMs) using Grad-CAM [61], which is commonly applied to localize the discriminative regions for image classification. We compare the CAMs calculated on the last feature maps of ScaleNet103(5.08M, 5.26G, 30.46%), ResNet101(44.54M, 7.83G, 24.10%), and DenseNet161(28.68M, 7.79G, 23.97%), where M and G...
TABLE 4: Comparison of different up-/down-sampling methods on Error rates(%), FLOPs(G) and inference Time(s).

<table>
<thead>
<tr>
<th>Model</th>
<th>Params</th>
<th>A + B</th>
<th>Error</th>
<th>FLOPs</th>
<th>Time</th>
<th>A + D</th>
<th>Error</th>
<th>FLOPs</th>
<th>Time</th>
<th>C + D</th>
<th>Error</th>
<th>FLOPs</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>ScaleNet124-D_{30}</td>
<td>1.8M</td>
<td>5.5</td>
<td>0.63</td>
<td>0.058</td>
<td>5.7</td>
<td>0.63</td>
<td>0.063</td>
<td>5.1</td>
<td>(0.4)</td>
<td>1.00</td>
<td>(58%)</td>
<td>0.089</td>
<td>(53%)</td>
</tr>
<tr>
<td>ScaleNet80-D_{5}D_{8}S_{10}</td>
<td>5.0M</td>
<td>5.9</td>
<td>0.37</td>
<td>0.025</td>
<td>5.8</td>
<td>0.37</td>
<td>0.027</td>
<td>5.2</td>
<td>(-0.7)</td>
<td>0.59</td>
<td>(59%)</td>
<td>0.036</td>
<td>(44%)</td>
</tr>
<tr>
<td>ScaleNet92-D_{11}D_{8}</td>
<td>4.0M</td>
<td>22.2</td>
<td>0.58</td>
<td>0.041</td>
<td>23.1</td>
<td>0.58</td>
<td>0.044</td>
<td>21.6</td>
<td>(-0.6)</td>
<td>0.90</td>
<td>(55%)</td>
<td>0.061</td>
<td>(49%)</td>
</tr>
<tr>
<td>ScaleNet92-D_{5}D_{10}S_{12}</td>
<td>6.0M</td>
<td>24.3</td>
<td>0.43</td>
<td>0.028</td>
<td>24.3</td>
<td>0.43</td>
<td>0.030</td>
<td>23.8</td>
<td>(-0.5)</td>
<td>0.69</td>
<td>(60%)</td>
<td>0.040</td>
<td>(43%)</td>
</tr>
</tbody>
</table>

TABLE 5: Comparison of different residual structures for ScaleNets on CIFAR-10 and CIFAR-100.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Model</th>
<th>SinglePath</th>
<th>MultiPath</th>
</tr>
</thead>
<tbody>
<tr>
<td>CIFAR-10</td>
<td>ScaleNet32 (1.0M)</td>
<td>6.96%</td>
<td>5.50%</td>
</tr>
<tr>
<td></td>
<td>ScaleNet98 (1.7M)</td>
<td>6.72%</td>
<td>5.06%</td>
</tr>
<tr>
<td>CIFAR-100</td>
<td>ScaleNet32 (1.0M)</td>
<td>29.09%</td>
<td>25.18%</td>
</tr>
<tr>
<td></td>
<td>ScaleNet98 (1.7M)</td>
<td>27.02%</td>
<td>23.24%</td>
</tr>
</tbody>
</table>

FIGURE 6: Classification results of all auxiliary classifiers and final main classifier.

refer to parameter scales and FLOPs, respectively. The last feature maps are just ahead of the final linear classifier, which can be regarded as the final output of a CNN-based feature extractor. ResNet101 and DenseNet161 are the pre-trained models provided by PyTorch. The images used all come from ImageNet [55].

a: Learning fine-grained features
Fig.7 shows the CAMs of the three networks on five different images with the same input size of 3x320x320. Clearly, the ScaleNet CAMs are very different from those of ResNet and DenseNet. ScaleNet tends to focus on the fine-grained details of an object, whereas ResNet and DenseNet always focus on a larger patch of an object. Under an input size of 3x320x320, the plane size of the final feature maps is 10x10 for ResNet and DenseNet but is 40x40 for ScaleNet. Therefore, the final feature maps of ScaleNet exhibit much higher resolution than those of ResNet and DenseNet, thus contributing to the capture of fine-grained visual features.

b: Multi-scale input analysis
Here, to conduct stronger comparative experiments, we input images with a very large size range (e.g., 32x32, 64x64, 128x128, 224x224, 256x256, 320x320, and 512x512) to the networks to compare their CAMs. Four different images are first stitched into a single image as the network input. The stitched image and related experimental results are shown in Fig.8, where goldfinches and fish are arranged on the diagonal.

Based on comparison of the ScaleNet CAMs on birds and fish, the activated regions of the birds and fish do not interfere with each other and are semantically independent. This suggests that the representation is not a physical representation based on image textures, but a semantic representation based on object categories. For the ScaleNet CAMs, when the input size decreases from 512x512 to 32x32, the activated regions of the large bird (top-left corner of each image) vary from small details to relatively large patches, and finally to some very large patches that cover the whole bird. This reveals the continuous changing process of semantic representation from fine granularity to coarse granularity. In other words, under a very large scale range from 512x512 to 32x32, ScaleNet always finds an appropriate semantic granularity to represent the object. Compared with ScaleNet, the DenseNet CAMs in Fig.8 (a, top) and Fig.8 (c) fail to reflect such a process.

Of note, the activated regions of the small birds (bottom-right of each image, shown in Fig.8 (a)) with ScaleNet exhibit much clearer activation morphology, with each small bird activated independently. However, the activated regions of these small birds (shown in Fig.8 (a, top) with DenseNet are blurry and quickly disappear as input size decreases. Comparing Fig.8 (b) with Fig.8 (c), when the input size is very small, the activated regions of the large bird and large fish with DenseNet begin to diffuse in the image plane, whereas the activated regions with ScaleNet always converge on the
In this paper, we realize image feature extraction based on an end-to-end and cascaded deconstruction-reconstruction process. A multipath residual structure is also proposed to improve the parameter efficiency of networks. Compared to the state-of-the-art networks, our ScaleNet achieves competitive performance under a trade-off between accuracy and efficiency. Furthermore, ScaleNet can remove the constraints between feature size and feature semantics, thereby realizing multiscale feature extraction at any network depth. ScaleNet combines high-resolution feature maps, fine-grained features, and strong semantic representation, thus hinting at a promising way in which to achieve unsupervised object detection.

ACKNOWLEDGMENT
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REFERENCES
DeConstruction Path: 
ReConstruction Path: 
DeConstruction Path: 
ReConstruction Path: 
V1 V2 V4
V1 V2 V4
Conv Conv DeConv DeConvConv Conv DeConv DeConv

cascaded DoubleCouple blocks

FIGURE 9: Expanding temporal information flow in visual cortices (a) to spatial domain of DoubleCouple blocks (b).

(a): visual cortices
(b): conv-deconv blocks

FIGURE 10: Comparison of CAMs between ScaleNet103(top) and DenseNet161(bottom) on traffic lights. (a): all images have been resized to 300x300 for display. (b): the original image has been resized to several different sizes with its h/w ratio unchanged. In both figures, real sizes are marked at the top/bottom in white (for ScaleNet) and cyan (for DenseNet).


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