Cross-layer Navigation Convolutional Neural Network for Fine-grained Visual Classification

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ABSTRACT

Fine-grained visual classification (FGVC) aims to classify sub-classes of objects in the same super-class (*e.g.*, species of birds, models of cars). For the FGVC tasks, the essential solution is to find discriminative subtle information of the target from local regions. Traditional FGVC models preferred to use the refined features, *i.e.*, high-level semantic information for recognition and rarely use low-level information. However, it turns out that low-level information which contains rich detail information also has effect on improving performance. Therefore, in this paper, we propose cross-layer navigation convolutional neural network for feature fusion. First, the feature maps extracted by the backbone network are fed into a convolutional long short-term memory model sequentially from high-level to low-level to perform feature aggregation. Then, attention mechanisms are used after feature fusion to extract spatial and channel information while linking the high-level semantic information and the low-level texture features, which can better locate the discriminative regions for the FGVC. In the experiments, three commonly used FGVC datasets, including CUB-200-2011, Stanford-Cars, and FGVC-Aircraft datasets, are used for evaluation and we demonstrate the superiority of the proposed method by comparing it with other referred FGVC methods to show that this method achieves superior results. <https://github.com/PRIS-CV/CN-CNN.git>

KEYWORDS

Computer vision, fine-grained visual classification, cross-layer navigation, convolutional long short-term memory, attention mechanism

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1 INTRODUCTION

Fine-grained visual classification (FGVC) works to distinguish sub-classes of a common visual super-class (*e.g.*, species of birds, models of cars, *etc.*). The difference of this task from the general image

classification lies in the finer granularity of the classes to which the image belongs. Since different sub-classes differ from each other only in subtle ways, the FGVC tasks face two challenges, *i.e.*, large intra-class variations and small inter-class difference. Hence, the commonly accepted solution is to mine discriminative information as much as possible from local regions for the FGVC tasks.

In this case, in the early work, researchers introduced strong supervisions to mine more discriminative information which requires the manual annotation information of the images, for example, object bounding boxes and part annotations [1, 12, 30]. Such methods first locate distinct regions based on additional annotation information, and then extract features from each of them. However, the fine-grained manual annotations of images are expensive and these methods are rarely used in practice. Subsequently, weakly supervision methods which we used in this paper locate discriminative regions with only class labels.

One of the representative class of methods used localization-classification subnetworks [3, 8, 20, 28] since every part of the object is important for learning discriminative information in the FGVC. They mainly locate discriminative regions through learning part detectors [32], attention mechanisms [4, 7, 9, 24, 31, 33], or filters/activations [13, 28]. Among them, the attention mechanism is widely used and the effect is very good. Many models like [5, 15, 22] attempt to incorporate attention mechanisms to improve the performance of CNNs in FGVC tasks. For example, the spatial transformation Network (STN) [15] proposed a learnable module that can be used to locate the most relevant regions in an image to the spatial domain, thus ignoring information from other weakly relevant less important regions. In addition, one way to learn discriminative regions is to integrate multi-level features and guide the features mutually by different levels [7].

Although the above study reports excellent results, the low-level information is sort of overlooked. As the depth of the network increases, the network pays more attention to global high-level abstract semantic information and some low-level detailed information is inescapably lost. In addition, spatio-temporal correlation between layers can refine the process of learning discriminative regions better. Thus, we introduce the ConvLSTM module which can effectively enhance this kind of correlation. In this paper, we propose cross-layer navigation convolutional neural network (CN-CNN), which aims to strengthen the connection between high-level (*i.e.*, semantic information) and low-level (*i.e.*, detailed information) and leverage them for better recognition. First, the feature maps extracted by the backbone network are fed into a convolutional long short-term memory (ConvLSTM) model sequentially from high-level to low-level to perform feature aggregation. Attention mechanisms are used after the feature fusion to extract spatial and

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Figure 1: Overall structure of the proposed CN-CNN. Two-pathway Hierarchy are introduced for cross-layer feature navigation in the FGVC. “S1”-“S5” mean stages in the backbone. “Att_i” and “Cls_i” indicate the attention mechanisms in the LH pathway and the classifiers.

Figure 2: Structure of the attention mechanisms.

channel information while linking high-level semantic information and low-level texture features, which can better locate the discriminative regions for the FGVC.

The major contributions of this work are summarized as follow:

- We propose the CN-CNN, which aims to strengthen the connection between high-level (*i.e.*, semantic information) and low-level (*i.e.*, detailed information) and leverage them for better recognition by ConvLSTM and attention mechanisms.
- Experimental results on three common FGVC datasets, including CUB-200-2011 [25], Stanford-Cars [16], and FGVC-Aircraft [21] datasets show that our proposed method can effectively improve the accuracy in the FGVC.

2 NETWORK STRUCTURE

In this section, we introduce the network architecture of proposed method in detail. The overall structure of is shown in Figure 1.

2.1 Two-pathway Hierarchy for Cross-layer Navigation

In this section, we use ResNet50 as the backbone for the feature extractor. The feature maps obtained by the third, fourth, and fifth stages are used as the input of the cross-layer navigation, noted as S3, S4, and S5, respectively. Two pathways are proposed, including high-low (HL) pathway, which navigates lower-level features by higher-level ones, and low-high (LH) pathway, which refines higher-level features with lower-level ones.

From high-level to low-level: The feature maps of different stages are sequentially inputted into ConvLSTM for the guidance from high-level to low-level. The features are aggregated to supervise the underlying texture features using the higher-level semantic features.

From low-level to high-level: The low-level feature maps then navigate the high-level ones by generating attention maps for them. In the right attention module, there also exists a pathway from low-level to high-level, which is used to deliver the information from the lower layers to the higher ones and link the channels better.

By this two pathway hierarchy structure, the network can well fuse the semantic feature information of the higher-level with the detail information of the lower-level, simultaneously.

Classifier: Finally, the feature maps M'_i learned from the two pathway are then fed into three independent classifiers for the FGVC. Each classifier contains a global average pooling (GAP) and two FC layers. The feature maps M'_i obtained by the LH pathway are then fed into the three layers to obtain predictions. And the final classification results are obtained by averaging predictions.

$$M'_i = M_i \cdot (SA \oplus CA), \quad (1)$$

Table 1: Comparison with state-of-the-art methods on three FGVC datasets. The best results are highlighted in bold.

Method	Base	Datasets		
		CUB-200-2011	Stanford Cars	FGVC-Aircraft
FT VGGNet (CVPR 18) [26]	VGG19	77.8	84.9	84.8
FT ResNet (CVPR 18) [26]	ResNet50	84.1	91.7	88.5
B-CNN (ICCV 15) [18]	VGG16	84.1	91.3	84.1
MA-CNN (ICCV 17) [33]	VGG19	86.5	92.8	89.9
NTS (ECCV 18) [29]	ResNet50	87.5	93.9	91.4
Cross-X (ICCV 19) [19]	ResNet50	87.7	94.6	92.6
DCL (CVPR 19) [6]	ResNet50	87.8	94.5	93.0
TASN (CVPR 19) [34]	ResNet50	87.9	93.8	-
CIN (AAAI 20) [10]	ResNet50	87.5	94.1	92.8
MC-Loss (TIP 20) [2]	ResNet50	87.3	93.7	92.6
CN-CNN (ours)	ResNet50	88.9	94.9	94.1

Table 2: Comparisons of models with/without the two-pathway hierarchy structure. HL: high-low pathway, LH: low-high pathway.

Method	Backbone	Accuracy(%)
Baseline	ResNet50	84.1
HL	ResNet50	86.6
HL+LH	ResNet50	87.2

where $\oplus$ represents the operation of addition which uses broadcasting and M_i represents the feature maps obtained after HL pathway, *i.e.*, ConvLSTM module.

2.2 ConvLSTM for Navigation from High-level to Low-level

Through previous work, we found that the results of some models can be effectively improved by introducing low-level features, even for simple aggregations [27]. Beyond that, we inspired by [14] that ConvLSTM is a very powerful module for connecting and integrating multiple layers of information. Therefore, we consider to introduce CONV LSTM module between multi-layer feature map to help feature fusion between different levels.

In our method, the feature maps of different stages obtained from backbone are first fed into corresponding upsampling operations and 1×1 convolution layers for obtaining exactly same sizes (*i.e.*, height, width, and channel numbers) of the feature maps. Then they are inputted into ConvLSTM from high-level to low-level. It takes on the role of connecting, guiding and merging different levels of features.

2.3 Attention Mechanisms for Navigation from Low-level to High-level

Here, we introduce both spatial and channel attention mechanisms in the navigation from low-level to high-level.

Spatial Attention (SA): As shown in Figure 1, different feature maps of the distinct levels are refined by attentions. The feature

Table 3: Comparisons of models with/without the ConvLSTM Module.

Method	Backbone	Accuracy(%)
w/o ConvLSTM	ResNet50	87.2
w/ ConvLSTM	ResNet50	88.9

maps are first resized into their original size. Then, they are fed into the SA module, respectively, to obtain the SA masks of different levels. The SA module contains one deconvolution operation with 3×3 kernel. The values of the SA masks are normalized into the interval of $[0, 1]$ by Sigmoid function, respectively and they can represent the importance of each region in the specific level.

$$SA = \sigma(\mathbf{k} * M_i), \quad (2)$$

where σ means the Sigmoid function, $*$ refers to the operation of deconvolution and $\mathbf{k}$ represents the convolution kernel.

Channel Attention (CA): Similarly, with the feature maps as inputs, the CA masks are obtained by a GAP and two FC layers. The channels of the feature maps of different levels are connected to each other and the information of the lower-level is passed from the bottom to the higher-level.

$$CA = \sigma(FC1 \cdot ReLU(FC2 \cdot GAP(M_i))), \quad (3)$$

where $FC1$ and $FC2$ represents the weights of two fully connected layers, σ and $ReLU$ refers to the Sigmoid and the ReLU function, respectively. And GAP refers to the global average pooling operation.

$$GAP(M_i) = \frac{1}{W \times H} \sum_{i=1}^H \sum_{j=1}^W M_i(i, j). \quad (4)$$

After obtaining both SA and CA masks, we aggregate them together for a pixel-wise masks and multiply the new masks onto the feature maps obtained by the HL pathway.

3 EXPERIMENTAL RESULTS AND DISCUSSION

We conducted experiments on three common FGVC datasets: Caltech-UCSD Birds (CUB-200-2011), Stanford-Cars, and FGVC-Aircraft datasets, which are widely used benchmarks for FGVC.

3.1 Implementation Details

We conducted all the experiments on GTX 1080Ti GPU, using Pytorch framework [23]. During training phase, images were resized to 448×448 which is a general setting. We used ImageNet-pretrained ResNet50 [11] as the backbone model. We took stochastic gradient descent (SGD) as the optimizer and used Batch Normalization for regularization. We trained the network for 300 epochs with initial learning rate as 0.001 for the backbone and 0.1 for the other modules. We set the momentum as 0.9 and the weight decay as 5×10^{-4} .

3.2 Comparisons with State-of-the-Art Methods

Table 1 shows the experiment results on CUB-200-2011, Stanford Cars, and FGVC-Aircraft datasets, trained with ResNet50 as the backbone model. The proposed method I obtains significant improvements on all the three datasets among the referred methods.

The referred methods listed in Table 1 are all weakly supervised methods conducted on the above three datasets. And when using ResNet50 as the backbone model to compare with these methods, the proposed method achieves better performance. In other words, it demonstrates the effectiveness of training networks with the cross-layer navigation. Among them, the proposed method produced especially better results on the CUB-200-2011 dataset that is even more difficult to identify.

3.3 Ablation Studies

The ablation studies were conducted on the CUB-200-2011 dataset with the ResNet50 as the backbone model. It aims to find out the impact of each component through comparative experiments.

Impact of the two-pathway hierarchy structure. To compare the performance of the networks with or without the two-pathway hierarchy structure, we conducted experiments in the baseline, the HL pathway, and the LH pathway. Here, we simply implemented the HL pathway with directly adding the feature maps together, which is same to the operation in feature pyramidal network [17]. In Table 2, we can find that there is 2.5% increase in the HL compared with the baseline, which is a significant improvement. Meanwhile, further adding the LH, the accuracy gains another about 0.6% improvement through the enhanced connection between features of different levels. The accuracies in the table clearly demonstrate the benefits of the two-pathway hierarchy structure.

Impact of the ConvLSTM Module. The difference between the proposed method and baseline (“HL+LH” in Table 2) is that ConvLSTM is introduced. As shown in Table 3, it is obvious that the accuracy obtained with the ConvLSTM is much higher than the baseline, with 1.7% performance improvement. This indicates that

Figure 3: Visualization of the output feature maps of the LH pathway. We randomly select three test images from one specific class on the CUB-200-2011 dataset. The bright white parts in the visualizations is the regions that the network especially pays attention to. In each rectangle, the left color image is the original image. In the right column, from top to bottom, they are high-level to low-level feature maps.

the ConvLSTM can well enhance the correlation between feature maps.

3.4 Visualizations

Parts of the visualizations of the attention module are shown in Figure 3. We randomly select three test images from one specific class on the CUB-200-2011 dataset. The bright white parts in the visualizations is the regions that the network especially pays attention to. It can be observed that the low-level information can capture more subtle parts to distinguish the birds. In the higher levels, the network focuses on abstract semantic information more. By integrating low-level information (e.g., colors, edge junctions, and texture patterns), performance can be improved with the enhanced feature representation and the model can accurately locate discriminative regions.

4 CONCLUSION

In this paper, we showed that for the FGVC tasks, it is an effective way to improve classification accuracy by using the cross-layer navigation for feature representation enhancement. We propose cross-layer navigation convolutional neural network (CN-CNN), which aims to strengthen the connection between high-level (i.e., semantic information) and low-level (i.e., detailed information) and leverage them for better recognition. Extensive experiments confirmed that the proposed method improves the accuracy on different FGVC datasets. The effectiveness of the components of the proposed method were also discussed. Visualizations can illustrate the ability of the cross-layer navigation.

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