Feature Boosting, Suppression, and Diversification for Fine-Grained Visual Classification

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Abstract—Learning feature representation from discriminative local regions plays a key role in fine-grained visual classification. Employing attention mechanisms to extract part features has become a trend. However, there are two major limitations in these methods: First, they often focus on the most salient part while neglecting other inconspicuous but distinguishable parts. Second, they treat different part features in isolation while neglecting their relationships. To handle these limitations, we propose to locate multiple different distinguishable parts and explore their relationships in an explicit way. In this pursuit, we introduce two lightweight modules that can be easily plugged into existing convolutional neural networks. On one hand, we introduce a feature boosting and suppression module that boosts the most salient part of feature maps to obtain a part-specific representation and suppresses it to force the following network to mine other potential parts. On the other hand, we introduce a feature diversification module that learns semantically complementary information from the correlated part-specific representations. Our method does not need bounding boxes/part annotations and can be trained end-to-end. Extensive experimental results show that our method achieves state-of-the-art performances on several benchmark fine-grained datasets.

Index Terms—fine-grained, visual classification, attention, feature diversification, part-specific feature

I. INTRODUCTION

Fine-grained visual classification (FGVC) focuses on distinguishing subtle visual differences within a basic-level category, e.g., species of birds [1] and dogs [2], and models of aircrafts [3] and cars [4]. Recently, convolutional neural networks (CNNs) have made great progress on many vision tasks, such as image caption [5], semantic segmentation [6], object detection [7] [8], etc. However, traditional CNNs are not powerful enough to capture the subtle discriminative features due to the large intra-class and small inter-class variations as shown in Fig. 1 which makes FGVC still a challenging task. Therefore, how to make CNNs locate the distinguishable parts and learn discriminative features are important issues that need to be addressed. Early works [9] [10] [11] [12] relied on predefined bounding boxes and part annotations to capture visual differences. However, collecting extra annotated information is labor-intensive and requires professional knowledge, which makes these methods less practical. Hence, researchers recently have focused more on weakly-supervised FGVC that only needs image labels as supervision. There are two paradigms towards this direction. One is based on part features, these methods [13] [14] [15] [16] [17] are often composed of two different subnetworks. Specifically, a localization subnetwork with attention mechanisms is designed for locating discriminative parts and a classification subnetwork is followed for recognition. The dedicated loss functions are designed to optimize both subnetworks. The limitation of these methods is that it is difficult to optimize because of the specially designed attention modules and loss functions. The other is based on high-order information, these methods [18] [19] [20] [21] [22] argue that the first-order information is not sufficient to model the differences and instead use high-order information to encode the discrimination. The limitation of these methods is that it takes up a lot of GPU resources and has poor interpretability.

We propose feature boosting, suppression, and diversifying towards both efficiency and interpretability. We argue that attention-based methods tend to focus on the most salient part, so other inconspicuous but distinguishable parts have no chance to stand out. However, the network will be forced to mine other potential parts when masking or suppressing the most salient part. Based on this simple and effective idea, we introduce a feature boosting and suppression module (FBSM), which highlights the most salient part of feature maps at the current stage to obtain a part-specific representation and sup-

Fig. 1. Illustration of large intra-class and small inter-class variations in FGVC. The images with large variations in each row belong to the same class. However, the images with small variations in each column belong to different classes. This situation is opposite to generic visual classification.
presses it to force the following stage to mine other potential parts. By inserting FBSMs into the middle layers of CNNs, we can get multiple part-specific feature representations that are explicitly concentrated on different object parts.

Intuitively, individual part-specific feature representation neglects the knowledge from the entire object and may not see the forest for the trees. To eliminate the bias, we introduce a feature diversification module (FDM) to diversify each part-specific feature representation. Specifically, given a part-specific representation, we enhance it by aggregating complementary information discovered from other parts. Through modeling the part interaction with FDM, we make the part-specific feature representation more discriminative and rich.

Finally, we jointly optimize FBSM and FDM as shown in Fig. 2. Our method does not need bounding boxes/part annotations and state-of-the-art performances are reported on several standard benchmark datasets. Moreover, our model is lightweight and easy to train as it does not involve the multi-crop mechanism [13] [23] [14].

Our contributions are summarized as follows:

- We propose a feature boosting and suppression module, which can explicitly force the network to focus on multiple discriminative parts.
- We propose a feature diversification module, which can model part interaction and diversify each part-specific representation.

II. RELATED WORK

Below, we review the most representative methods related to our method.

A. Fine-Grained Feature Learning

Ding et al. [17] proposed sparse selective sampling learning to obtain both discriminative and complementary regions. Sun et al. [24] proposed a one-squeeze multi-excitation module to learn multiple parts, then applied a multi-attention multi-class constraint on these parts. Zhang et al. [25] proposed to discover contrastive clues by comparing image pairs. Yang et al. [15] introduced a navigator-teacher-scrutinizer network to obtain discriminative regions. Luo et al. [26] proposed Cross-X learning to explore the relationships between different images and different layers. Gao et al. [27] proposed to model channel interaction to capture subtle differences. Li et al. [20] proposed to capture the discrimination by matrix square root normalization and introduced an iterative method for fast end-to-end training. Our method utilizes feature boosting and suppression to learn different part representations in an explicit way, which is significantly different from previous methods.

B. Feature Fusion

FPN [8] and SSD [7] aggregating feature maps from different layers have achieved great success in the object detection field. However, they use element-wise addition as the aggregation operation, making the capabilities of these methods still limited. Wang et al. [28] proposed a non-local operation that computes the response at a spatial position as a weighted sum of the features at all positions in the feature maps. SG-Net [29] utilized the non-local operation to fuse feature maps from different layers. CIN [27] adopted the non-local operation to mine semantically complementary information from different feature channels. Our FDM is similar with [29] and [27], but there are essential differences: (1) SG-Net tends to explore positive correlations to capture long-range dependencies, while FDM tends to explore negative correlations to diversify the feature representation. (2) A feature diversification module (FDM) aiming at modeling part interaction to enhance each part-specific representation.

A. Feature Boosting and Suppression Module

Given feature maps \( X \in R^{C \times W \times H} \) from a specific layer, where \( C, W, H \) represents the number of channels, width and height respectively. We split \( X \) evenly into \( k \) parts along width dimension [30] and denote each striped parts as \( X_{(i)} \in R^{C \times (W/k) \times H}, i \in [1, k] \). Then we employ a \( 1 \times 1 \) convolution \( \phi \) to explore the importance of each part:

\[
A_{(i)} = \text{Relu}(\phi(X_{(i)})) \in R^{1 \times (W/k) \times H}
\]

The nonlinear function \( \text{Relu} \) is applied to remove the negative activations. \( \phi \) is shared among different striped parts and acts as a grader. We then take the average of \( A_{(i)} \) as the importance factor \( b'_i \) for \( X_{(i)} \), i.e.,

\[
b'_i = \text{GAP}(A_{(i)}) \in R
\]

where \( \text{GAP} \) denotes global average pooling. We use softmax to normalize \( B' = (b'_1, \cdots, b'_k)^T \):

\[
b_i = \frac{\exp(b'_i)}{\sum_{j \in [1,k]} \exp(b'_j)}
\]

With the normalized importance factors \( B = (b_1, \cdots, b_k)^T \), the most salient part can be determined immediately. We then obtain the boosting feature \( X_b \) by boosting the most salient part:

\[
X_b = X + \alpha \ast (B \otimes X)
\]

where \( \alpha \) is a hyper-parameter, which controls the extent of boosting, \( \otimes \) denotes element-wise multiplication. A convolutional layer \( h \) is applied on \( X_b \) to get a part-specific representation \( X_p \):

\[
X_p = h(X_b)
\]

By suppressing the most striped part, we can obtain the suppression feature \( X_s \):

\[
X_s = S \otimes X
\]
B. Feature Diversification Module

As learning discriminative and diverse feature plays a key role in FGVC [32] [24] [23], we propose a feature diversification module, which enhances each part-specific feature by aggregating complementary information mined from other part-specific representations.

We first discuss how two part-specific features diversify each other with the pairwise complement module (PCM). A simple illustration of PCM is shown in Fig. 4. Without loss of generality, we denote two different part-specific features as $X_{p_1} \in R^{C \times W_1 \times H_1}$ and $X_{p_2} \in R^{C \times W_2 \times H_2}$, where $C$ denotes the number of channels, $W_1 H_1$ and $W_2 H_2$ denote their spatial size respectively. We use subscript $p_i$ to denote that $X_{p_i}$ focuses on the $i^{th}$ part of the object and will omit the subscript when there is no ambiguity. We denote the feature vector at each spatial position along channel dimension as a pixel, i.e.,

$$\text{pixel}(X, i) = (X_{1,i}, \cdots, X_{C,i})^T \quad (8)$$

We first calculate the similarities between pixels in $X_{p_1}$ and pixels in $X_{p_2}$:

$$M = f(X_{p_1}, X_{p_2}), \quad f(X, Y) = X^T Y \quad (9)$$

Here, we use inner product to compute the similarity. The element $M_{i,j}$ represents the similarity of the $i^{th}$ pixel of $X_{p_1}$ and the $j^{th}$ pixel of $X_{p_2}$. The lower the similarity of two pixels is, the more complementary they are, so we adopt $-M$ as the complementary matrix. Then we operate normalization on $-M$ row-wise and column-wise respectively:

$$A_{p_1} = \text{softmax}(-M) \in [0, 1]^{W_2 H_2 \times W_1 H_1} \quad (10)$$

$$A_{p_2} = \text{softmax}(-M) \in [0, 1]^{W_1 H_1 \times W_2 H_2} \quad (11)$$

where $S = (s_1, \cdots, s_k)^T$, $\beta$ is a hyper-parameter, which control the extent of suppressing.

In short, the functionality of FBSM can be expressed as: FBSM($X$) = ($X_{p_1}, X_s$). Given feature maps $X$, FBSM outputs part-specific feature $X_p$ and potential feature maps $X_s$. Since $X_s$ suppresses the most salient part in current stage, other potential parts will stand out after feeding $X_s$ into the following stage. A diagram of the FBSM is shown in Fig. 3.

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where softmax is performed column-wise. Then we can get the complementary information:

\[
Y_{p1}^{p2} = X_{p2}A_{p2}^T \in R^{C \times W_1 \times H_1}
\]

(12)

\[
Y_{p1}^{p2} = X_{p1}A_{p2}^T \in R^{C \times W_2 \times H_2}
\]

(13)

where \(Y_{p1}^{p2}\) denotes the complementary information of \(X_{p1}\) relative to \(X_{p2}\). It is worth noting that each pixel of \(Y_{p1}^{p2}\) can be written as:

\[
\text{pixel}(Y_{p1}^{p2}, i) = \sum_{j \in [1,W_2,H_2]} (A_{p2})_{i,j} \times \text{pixel}(X_{p2}, j)
\]

(14)

i.e., each pixel of \(Y_{p1}^{p2}\) takes all pixels of \(X_{p2}\) as references, and the higher the complementarity between \(X_{p2}, i\) and \(X_{p2}, j\), the greater the contribution of \(X_{p2}, j\) to \(Y_{p1}^{p2}, i\). In this way, every pixel in these two part-specific features can mine semantically complementary information from each other.

Now we discuss the general case. Formally, given a collection of part-specific features \(P = \{X_{p1}, X_{p2}, X_{p3}, \ldots, X_{pn}\}\), the complementary information of \(X_{pi}\) is:

\[
Y_{pi} = \sum_{X_{pj} \in P \land i \neq j} Y_{pj}^{pi}
\]

(15)

where \(Y_{pj}^{pi}\) can be obtained by applying \(X_{pi}\) and \(X_{pj}\) on (9), (10), and (12). In practice, we can compute \(Y_{pj}^{pi}\) and \(Y_{pi}^{pj}\) simultaneously as shown in Fig. 4. Then we get the enhanced part-specific feature:

\[
Z_{pi} = X_{pi} + \gamma \times Y_{pi}
\]

(16)

where \(\gamma\) is a hyper-parameter, which controls the extent of diversification.

**C. Network Design**

Our method can be easily implemented on various convolutional neural networks. As shown in Fig. 2, we take Resnet as the backbone in our experiment. The feature extractor of Resnet has five stages and the spatial size of feature maps is halved after each stage. Considering that the deep layers have more semantic information, we plug FBSMs into the end of stage3, stage4, stage5. The different part-specific representations generated by FBSMs are fed into FDM to diversify each representation. Our method is highly customizable, it can adapt to different granularities of classification by adjusting the number of FBSMs directly.

At training time, we compute the classification loss for each enhanced part-specific feature \(Z_{pi}\):

\[
L_{cls}^{i} = -y^T \log(p_i), \quad p_i = \text{softmax} (\text{cls}_i(Z_{pi}))
\]

(17)

where \(y\) is the ground-truth label of the input image and represented by one-hot vector, \(\text{cls}_i\) is a classifier for the \(i\)th part, \(p_i \in R^N\) is the prediction score vector, \(N\) is the number of object categories. The final optimization objective is:

\[
L = \sum_{i=1}^{T} L_{cls}^{i}
\]

(18)

where \(T = 3\) is the number of enhanced part-specific features. At inference time, we take the average of prediction scores for all enhanced part-specific features as the final prediction result.

**IV. EXPERIMENTS**

**A.Datasets and Baselines**

We evaluate our model on four commonly used datasets: CUB-200-2011 [1], FGVC-Aircraft [3], Stanford Cars [4], Stanford Dogs [2]. The details of each dataset can be found in Table I. We compare our model with following baselines due to their state-of-the-art results. All baselines are listed as follows:

- **Part-RCNN** [9]: proposes geometric constraints on mined semantic parts to normalize the pose.
- **DeepLAC** [10]: integrates part localization, part alignment, and classification in one deep neural network.
- **S3N** [17]: learns to mine discriminative and complementary parts to enhance the feature learning.
- **API-Net** [23]: proposes an attentive pairwise interaction network to identify differences by comparing image pairs.
- **NTS** [15]: guides region proposal network by forcing the consistency between informativeness of the regions and their probabilities being ground-truth class.
- **MGE-CNN** [16]: learns a mixture of granularity-specific experts to capture granularity-specific parts.
- **DCL** [34]: learns to destruct and construct the image to acquire the expert knowledge.
- **MAMC** [24]: applies the multi-attention multi-class constraint in a metric learning framework to mine parts.
- **MA-CNN** [32]: makes part mining and fine-grained features learning in a mutual reinforced way.

**TABLE I**

FOUR FINE-GRAINED DATASETS COMMONLY USED IN FGVC.

| Dataset             | Name       | #Class | #Train | #Test  |
|---------------------|------------|--------|--------|--------|
| CUB-200-2011        | Bird       | 200    | 5994   | 5794   |
| FGVC-Aircraft       | Aircraft   | 100    | 6667   | 3333   |
| Stanford Cars       | Car        | 196    | 8144   | 8041   |
| Stanford Dogs       | Dog        | 120    | 12000  | 8580   |
We use PyTorch to implement our experiments. The backbone, MA-CNN, is set to 0.002, and the newly added layers are set to 0.00001, mini-batch of 20. The learning rate of the backbone, our model is 2.7%, 1.5%, 1.3%, 0.1%, 0.1% higher than them respectively. DCL spots discriminative parts by filtration and distillation learning. Compared with API-Net and Cross-X, which both take image differences, our method outperforms them by large margins. DTB-Net explore high-order information to capture the subtle differences, our method outperforms them by large margins. Compared with API-Net and Cross-X, which both take image pairs as input and model the discrimination by part interaction, our model gets 1.6% improvements. The accuracy of our method is 3.1% higher than MAMC, which formulates part re-detection as input at the second stage, our model is 4.0%, 1.8%, 0.8% higher than them respectively. ISQRT-COV and MGE-CNN, which all take the raw image as input at the first stage to explore informative regions and takes them as input at the second stage, our model is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and DTL, which all take the raw image as input at the first stage, our model is 4.0%, 1.8%, 0.8% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 7.7% higher than them. Compared with the two-stage methods: RA-CNN, NTS, MGE-CNN, S3N, and FDL, which all take the raw image as input at the first stage to explore informative regions and takes them as input at the second stage, our model is 4.0%, 1.8%, 0.8% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MGE-CNN, which all take the raw image as input at the first stage to explore informative regions and takes them as input at the second stage, our model is 9.0%, 1.8%, 0.8% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our model is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively.

### B. Implementation Details

We validate the performance of our method on Resnet50 and Resnet101 [33], which are all pre-trained on the ImageNet dataset [37]. We insert FBSMs at the end of stage3, stage4 and stage5. During training, the input images are resized to 550 × 550 and randomly cropped to 448 × 448. We apply random horizontal flips to augment the trainset. During testing, the input images are resized to 550 × 550 and cropped from center into 448 × 448. We set hyper-parameters $\alpha = 0.5$, $\beta = 0.5$ and $\gamma = 1$.

Our model is optimized by Stochastic Gradient Descent with the momentum of 0.9, epoch number of 200, weight decay of 0.00001, mini-batch of 20. The learning rate of the backbone layers is set to 0.002, and the newly added layers are set to 0.02. The learning rate is adjusted by cosine anneal scheduler [38]. We use PyTorch to implement our experiments.

### C. Comparison with State-of-the-Art

The top-1 classification accuracy on CUB-200-2011 [1], FGVC-Aircraft [3], Stanford Cars [4] and Stanford Dogs [2] datasets are reported in Table II.

#### Results on CUB-200-2011: CUB-200-2011 is the most challenging benchmark in FGVC, our models based on Resnet50 and Resnet101 both achieve the best performances on this dataset. Compared with DeepLAC and Part-RCNN which use predefined bounding boxes/part annotations, our method is 9.0%, 7.7% higher than them. Compared with the two-stage methods: RA-CNN, NTS, MGE-CNN, S3N, and FDL, which all take the raw image as input at the first stage to explore informative regions and takes them as input at the second stage, our model is 4.0%, 1.8%, 0.8% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively. ISQRT-COV and MA-CNN, which use predefined bounding boxes/part annotations, our method is 9.0%, 1.8%, 0.8%, 0.8%, 0.7% higher than them respectively.

#### Results on FGVC-Aircraft: Our method gets competitive results on this dataset. Compare with RA-CNN and MA-CNN, our method exceeds them by large margins. With Resnet50 backbone, our model is 2.7%, 1.5%, 1.3%, 0.1%, 0.1% higher

| Methods | Backbone | I-Stage | CUB-200-2011 | FGVC-Aircraft | Stanford Cars | Stanford Dogs |
|---------|----------|---------|--------------|---------------|---------------|---------------|
| DeepLAC | VGG      | ×       | 80.3         | -             | -             | -             |
| Part-RCNN | VGG | ×       | 81.6         | -             | -             | -             |
| RA-CNN  | VGG      | ×       | 85.3         | 88.1          | 92.5          | 87.3          |
| MA-CNN  | VGG      | √       | 86.5         | 89.9          | 92.8          | -             |
| MAMC    | Resnet50 | √       | 86.2         | -             | 92.8          | 84.8          |
| NTS     | Resnet50 | ×       | 87.5         | 91.4          | 93.3          | -             |
| API-Net | Resnet50 | √       | 87.7         | 93.0          | 94.8          | 88.3          |
| Cross-X | Resnet50 | √       | 87.7         | 92.6          | 94.5          | 88.9          |
| DCL     | Resnet50 | √       | 87.8         | 93.0          | 94.5          | -             |
| DTL     | Resnet50 | √       | 87.5         | 91.2          | 94.1          | -             |
| CIN     | Resnet50 | √       | 87.5         | 92.6          | 94.1          | -             |
| LIO     | Resnet50 | √       | 88.0         | 92.7          | 94.5          | -             |
| ISQRT-COV | Resnet50 | √       | 88.1         | 90.0          | 92.8          | -             |
| MGE-CNN | Resnet50 | ×       | 88.5         | -             | 93.9          | -             |
| S3N     | Resnet50 | ×       | 88.5         | 92.8          | 94.7          | -             |
| FDL     | Resnet50 | ×       | 88.6         | 93.4          | 94.3          | 85.0          |
| FDL     | Resnet50 | ×       | 88.6         | 93.4          | 94.3          | 85.0          |
| Ours    | Resnet50 | √       | 89.5         | 93.1          | 95.0          | 89.4          |
| MAMC    | Resnet101 | √       | 86.5         | -             | 93.0          | 85.2          |
| DTB-Net | Resnet101 | √       | 88.1         | 91.6          | 94.5          | -             |
| CIN     | Resnet101 | √       | 88.1         | 92.8          | 94.5          | -             |
| API-Net | Resnet101 | √       | 88.6         | 93.4          | 94.9          | 90.3          |
| ISQRT-COV | Resnet101 | √       | 88.7         | 91.4          | 93.3          | -             |
| MGE-CNN | Resnet101 | ×       | 89.4         | -             | 93.6          | -             |
| Ours    | Resnet101 | √       | 89.5         | 93.1          | 95.0          | 89.4          |

TABLE II

Comparison with state-of-the-art methods on four fine-grained benchmark datasets. ‘-’ means the result is not mentioned in the relevant paper.
than ISQRT-COV, DTB-Net, NTS, Cross-X, and CIN respectively. LIO that enhances feature learning by modeling object structure obtains the same result as our model. Our model is 0.1%, 0.3%, 0.3%, 0.7% lower than S3N, DCL, API-Net and FDL. However, S3N and FDL are both two-stage methods whereas our method is one-stage and more efficient. DCL destructs the image to locate discriminative regions, but it is not easy to define what level of destruction is appropriate. API-Net needs to consider different pairwise image combinations and requires large computing resources.

**Results on Stanford Cars:** Our method equipped with Resnet101 gets the best result on this dataset. Our method exceeds RA-CNN and MA-CNN which use VGG [39] as backbone by large margins. With Resnet50 backbone, our method is higher than ISQRT-COV, MAMC, NTS, MEG-CNN, DTB-Net, CIN, and FDL but lower than DCL, LIO, Cross-X, S3N, and API-Net. We suspect that features extracted from shadow layers (stage_3, stage_4) lack rich semantic information, which may cause degradation of recognition performance. When deepening the network and taking Resnet101 as the backbone, we obtain the best result of 95.0%.

**Results on Stanford Dogs:** Most previous methods do not report results on this dataset because of the computational complexity. Our method exceeds RA-CNN and MA-CNN which use VGG [39] as backbone by large margins. With Resnet50 backbone, our method is higher than ISQRT-COV, MAMC, NTS, MEG-CNN, DTB-Net, CIN, and FDL but lower than DCL, LIO, Cross-X, S3N, and API-Net. We suspect that features extracted from shadow layers (stage_3, stage_4) lack rich semantic information, which may cause degradation of recognition performance. When deepening the network and taking Resnet101 as the backbone, we obtain the best result of 95.0%.

**D. Ablation Studies**

We perform ablation studies to understand the contributions of each proposed module. We take experiments on four datasets with Resnet50 as backbone. The results are reported in Table [III].

| Methods               | Bird  | Aircraft | Car   | Dog   |
|-----------------------|-------|----------|-------|-------|
| Resnet50              | 85.5  | 90.3     | 89.8  | 81.1  |
| Resnet50+FBSM         | 88.9  | 92.4     | 94.0  | 87.5  |
| Resnet50+FBSM+FDM     | 89.3  | 92.7     | 94.4  | 88.2  |

**The effect of FBSM:** To obtain multiple discriminative part-specific feature representations, we insert FBSMs at the end of stage_3, stage_4 and stage_5 of Resnet50. With this module, the accuracy of Bird, Aircraft, Car, and Dog increased by 3.4%, 2.1%, 4.2%, and 6.4% respectively, which reflects the effectiveness of the FBSM.

**The effect of FDM:** When introducing FDM into our approach to model part interaction, the classification results on Bird, Aircraft, Car, and Dog datasets increased by 0.4%, 0.3%, 0.4%, and 0.7% respectively, which indicates the effectiveness of the FDM.

**E. Visualization**

We visualize the activation maps taken from Resnet50 with and without FBSMs on four benchmark datasets. As shown in Fig., for each raw image sampled from four datasets, the activation maps at the first to third columns correspond to the third to fifth stages of Resnet50 respectively. We can observe that the network tends to focus on the most salient part without FBSMs and is forced to mine different parts when equipped with FBSMs. Taking the bird as an example, without FBSMs, the features at different stages all focus on the swing. When there are FBSMs, the features in stage_3 focus on the swing, the features in stage_4 focus on the head, and the features in stage_5 focus on the tail. The visualization experiments prove the capability of FBSMs for mining multiple different discriminative object parts.

**V. CONCLUSION**

In this paper, we propose to learn feature boosting, suppression, and diversification for fine-grained visual classification. Specifically, we introduce two lightweight modules:
One is the feature boosting and suppression module which boosts the most salient part of the feature maps to obtain the part-specific feature and suppresses it to explicitly force following stages to mine other potential parts. The other is the feature diversification module which aggregates semantically complementary information from other object parts to each part-specific representation. The synergy between these two modules helps the network to learn more discriminative and diverse feature representations. Our method can be trained end-to-end and does not need bounding boxes/part annotations. The state-of-the-art results are obtained on several benchmark datasets and ablation studies further prove the effectiveness of each proposed module.

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