Visual Tree Convolutional Neural Network in Image Classification

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Abstract—In image classification, Convolutional Neural Networks (CNN) models have achieved high performance with the rapid development in deep learning. However, some categories in the image datasets are more difficult to distinguished than others. Improving the classification accuracy on these confused categories is beneficial to the overall performance. In this paper, we build a Confusion Visual Tree (CVT) based on the confused semantic level information to identify the confused categories. With the information provided by the CVT, we can lead the CNN training procedure to pay more attention on these confused categories. Therefore, we propose Visual Tree Convolutional Neural Networks (VT-CNN) based on the original deep CNN models. We evaluate our VT-CNN model on the benchmark datasets CIFAR-10 and CIFAR-100. In our experiments, we build up 3 different VT-CNN models and they obtain improvement over their based CNN models by 1.36%, 0.89% and 0.64%, respectively.

I. INTRODUCTION

The CNN models are widely used in image classification tasks and their performance is better than any other traditional methods [1]. Though the classification accuracy of the state-of-the-art model is surpassing that of human beings, there still remains a challenge that it is difficult for CNN models to discriminate the categories with high visual similarity. We know that some instances are difficult to distinguish while they come from different categories. The misclassification between instances from these categories makes a great contribution to the remaining error rate of CNN models. Take categories in the ImageNet [2] dataset as an example. We consider a coarse-grained category set "Dog" and the fine-grained categories which contain 120 different dog species such as "Basenji", "Pembroke" and "Cardigan" in this set. Compared with the coarse-grained category sets, the fine-grained categories in each set have strong visual confusion [3]. We can easily distinguish two coarse-grained category sets such as "Dog" and "Chariot", but it is difficult to discriminate the 120 fine-grained categories in "Dog" set.

There are two reasons for this problem. The one is that the structure of the CNN models may be the limitation of the performance. The structure may be not deep enough to get the higher performance. The other is that the strategy which guides the training of the CNN models is not fit with the fine-grained categories classification in image classification tasks. In this paper, we try to resolve the problem caused by the latter reason. The original CNN models output predictions of all the categories in the dataset at once, which means the models actually treat these categories equally. Therefore, the confused fine-grained categories mentioned above make the distinguishing ability of the original CNN models encounter a bottleneck.

Some traditional methods [4][5] based on the tree structure are proposed to deal with the problems caused by the confused categories. These traditional methods put coarse-grained categories to low-level layers of the tree structure and fine-grained categories to high-level layers. On the one hand, the benefit is that coarse-grained categories are easily to distinguished so the tree classifiers can finish this classification quickly and effectively. On the other hand, the tree classifiers can mainly focus on different sets of fine-grained categories, which is the most difficult part of the classification tasks.

Inspired by the tree classifier methods, we can also combine CNN models with the tree structure to deal with the problem of imbalance among quantities of image categories. Our idea is to construct new CNN models by embedding a visual tree constructed on categories in the dataset into original CNN models. We utilize the visual tree to guide the training of the CNN models. We want the CNN models mainly focus on the category of one sample and the confused categories of it when doing the fine-grained categories classification. Notice that we can get the confused categories from the fine-grained categories on the high-level layers of the visual tree. Different with the tree classifier, our CNN models should output predictions of all the categories in the dataset instead of a part of that, which means that our models focus on the confused categories of one sample while inhibiting other categories. Therefore, we need the outputs from coarse-grained categories classification of our CNN models. We can achieve it by utilizing the coarse-grained categories on the low-level layers in the visual tree.

Considering the issues mentioned above, we should firstly construct a visual tree structure in order to provide the coarse-grained categories and the fine-grained category separations for CNN models. Then we should change the structure of the original CNN models aiming to fit with the fine-grained confused categories classification in the image classification tasks. In this paper, we propose a novel scheme that combining a visual tree structure to the CNN model and we name it Visual Tree Convolutional Neural Network (VT-CNN). The
Our VT-CNN model has a more simple network structure compared to the H-CNN model. This is mainly because the VT-CNN model focuses on the hierarchical structure of image categories directly from the output from CNN models. In the H-CNN model, outputs multiple predictions ordered from coarse-grained to fine-grained along the concatenated convolutional layers corresponding to the hierarchical structure of the target categories, which can be regarded as a form of prior knowledge on the output. However, the HD-CNN model has to pretrain the shared layers and fine-tune the pre-trained models on fine-grained category components several times, which is much complicated and there is no close connection between the coarse-grained category branches and the fine-grained category branch in the B-CNN model except for their loss weights.

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compared with the HD-CNN model so we can train VT-CNN without fine-tuning the pre-trained models and we use a new loss function in the fine-grained category branch in order to connect all the branches closely.

III. METHOD

We explain the overview of our new image classification method called VT-CNN. First we introduce the method to construct CVT. Then we describe the details of VT-CNN.

A. Establish a Confusion Visual Tree

The goal of this stage is to construct the visual tree for the VT-CNN model. The tree structure in our VT-CNN model, which we call it Confusion Visual Tree, is established in three steps as follows. The first is using the confusion graph generation algorithm \[3\] to compute confusion graph and its weights. The second is using the community hierarchical detection algorithm \[14\] to generate communities in the confusion graph. The last is building a CVT by utilizing the results of the second step.

Here we talk about the details in the construction of the CVT. We apply the confusion graph generation function to generate a confusion graph which is shown at the Initial step. Each vertex represents one category in the dataset and the weight of each edge quantifies the confusion between two connected categories. Then we apply the community hierarchical detection function on the confusion graph and we get a community graph at each iteration of this function. At Iter. 1 step, for instance, we get five fine-grained communities and we set five nodes to the tree in "level3" which correspond to the communities one by one. Each member of one of the communities refers to a specific category. Then we link the leaves to level3 nodes. For instance, we link node “cat” and node “dog” to node “Small-mammals” in level3. We repeat it until nodes in level2 are linked to root node in level1 and then we finish the construction process.

B. VT-CNN Architecture

In this section, we embed the CVT into an original CNN model to construct the VT-CNN model. Take the classification task on CIFAR-100 as an example, the architecture of the VT-CNN model is shown in Fig. 1(a) and the 4 levels CVT of CIFAR-100 is in Fig. 1(b). The goal of the VT-CNN model is to distinguish the fine-grained categories presented as leaves of the tree structure, which are the final targets of the classification task. For the tree structure, we use level-\(n\) to refer to the \(n\)th layer of the visual tree. We define that level-1 refers to the root node and level-\(N\) refers to the leaves of the tree which has \(N\) layers.

The VT-CNN model is based on an existing CNN model. It has two important components. The one is the trunk layers, which we called the base architecture. The other is the branch layers and we name them branch architecture. The
base architecture is actually borrowed from an original CNN model such as the AlexNet model and the VGG-Verydeep-16(VGG16) model and the layers in it are shared by all of the branches. The branch architecture is related to different levels of the visual tree. The architecture in each branch contains two ConvNets and two FC layers and each branch is associated with a discrimination task for its related level in the tree architecture. The number of the layers in the branch architecture is equal to the number of the levels in the visual tree without the root level. Followed [6], low layers in CNN models usually capture the low level features of an image such as basic shapes while higher layers are likely to extract higher level features such as the face of the dog. Similar to this conception, the coarse-grained categories on low level of the tree architecture is associated with the low level features mentioned above while the fine-grained categories on leaves with the high level features. Therefore, the branch layers which are extended from low layers in CNN models are associated with the low level in the tree architecture while high layers with high level in the tree architecture.

The tree structure of the VT-CNN model provides the prior information contained in branches of low layers for fine-grained categories classification in the last branch of high layers. It is benefit from the conception that the information on the leaves of a tree structure which is the key to the fine-grained classification is actually contained in their ancestors which is responsible for the coarse-grained classification. Therefore, our VT-CNN focuses on the fine-grained categories in same communities instead of treating all the categories equally, which is different to original CNN models.

C. VT-CNN Training

The idea of our VT-CNN model is that the prior information of the coarse-grained categories classification should be used for the fine-grained categories classification. So we split the training of our VT-CNN into three steps which are the establishing of the CVT, the training of coarse-grained branches and the training of the fine-grained branch.

1) Establish a Confusion Visual Tree for a Specific CNN model: We firstly establish a CVT for a CNN model which is used as the basic CNN model of our VT-CNN model. Firstly, we train the original CNN model on a specific dataset and we get its outputs which are scores on each category of images in the dataset. Then we use the algorithm from Section III-A to establish the CVT based on these outputs.

2) Training Data: In order to train the VT-CNN model, there should be some changes in the original dataset. Each image should have several labels which are consistent with the coarse-grained and fine-grained category divisions based on the CVT constructed in Section III-C. The number of the labels is equal to the number of branches in the VT-CNN model. Take an image whose label is "dog" in CIFAR-10 as an example, the image has three labels which are "Animal", "Small-mammals", "Dog" according to the rule mentioned above.

3) Train the Coarse-grained Branches: All the branches except for the last branch which is associated with the fine-grained categories classification are training in this step. We give the loss function directly. The loss function in the training of the VT-CNN model contains all the loss function in coarse-grained branches. The loss function is defined as:

$$L_C = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{K} W_k \log \left( \frac{e^{y_{ik}}}{\sum_j e^{y_{ij}}} \right)$$  \hspace{1cm} (1)$$

where $i$ denotes the $i$th sample in the mini-batch, $K$ is the number of all the branches in the VT-CNN model, $W_k$ is the loss weight of $k$th branch contributing to the loss function and $c_j$ denotes the $j$th element in the vector $c$ of class scores. Notice that we have no need to consider the last branch in this section so the number of the branches is from $k = 1$ to $k = K - 1$. This loss function $L_C$ computes the softmax cross-entropy on these branches and add them together.

4) Train the Fine-grained Branch: After the coarse-grained branches are properly trained, we start training the fine-grained branch which is also the last branch of the VT-CNN model. In the probabilistic averaging layer, we change the final prediction into a weighted average prediction which is computed from the $(K-1)$th coarse-grained branch as below:

$$f_i = \frac{\sum_{j=1}^{K-1} f_{ij} W_j}{\sum_{j} f_{ij} W_j}$$  \hspace{1cm} (2)$$

where $t$ is the fine-grained category to the $(K - 1)$th coarse-grained category set so $t(i)$ denotes the related coarse-grained category of the fine-grained category $i$.

The loss function of the fine-grained branch is defined as:

$$L_F = -\frac{1}{n} \sum_{i=1}^{n} W_K \log \left( \frac{e^{f_{ik}}}{\sum_j e^{f_{ij}}} \right)$$  \hspace{1cm} (3)$$

During the training process, we change the weight $W_k$ to control that which branch is going to be trained. In our training strategy, we want to train the coarse-grained branches firstly so we firstly set $\sum_{k=1}^{K-1} W_k = 1$ and $W_K = 0$. Then we train the fine-grained branch and we set $\sum_{k=1}^{K-1} W_k = 0, W_K = 1$. Finally, we finish the training process.

IV. EXPERIMENT

A. Datasets and Experiment Settings

To comprehensively evaluate our proposed method, the following two image datasets are used in our experiment: CIFAR-10 and CIFAR-100.

The CIFAR-10 is a dataset for general object recognition which has 10 categories. Each image is natural RGB with 32×32 pixels and the dataset has 60000 images in total. 50000 for training and 10000 for testing. The CIFAR-100 dataset has 60000 images and 100 categories in total. Each image is natural RGB with 32 × 32 pixels and each category has 600 images in which 500 for training and 100 for evaluating. Our experiment on these two datasets follows their division.
The Top-1 Mean Accuracy (%) is used as the criterion to evaluate the performance of all these approaches. A PC with Intel Core i7, 32GB memory and NVIDIA GeForce GTX 1080 Ti is utilized to run all the experiments.

### B. CIFAR-10

Experiments on CIFAR-10 dataset compare the VT-CNN models with base models and the B-CNN [6] models.

We construct two baseline models. The Base A model is actually the AlexNet [1] model and there is just a little different between them that the size of filters in the first and second convolutional layers of the Base A model is adapted to $5 \times 5$. The Base B model is the VGG16 [7] model without the final max-pooling layer because images in the CIFAR dataset are very small.

Then we construct VT-CNN models based on the baseline models. In CIFAR-10 dataset, our CVT model has 4 hierarchical layers so there are 3 branches in VT-CNN models. The specific configuration is shown in Table I.

We evaluate our VT-CNN model, their base models and the B-CNN models on CIFAR-10 dataset. Notice that the tree structure of the B-CNN model is the same as that in our VT-CNN model. For model A, both models’ learning rates are initialized to be 0.003 and decrease to 0.0005 after 40 epochs and 0.0001 after 50 epochs. For model B, we fine-tune on the pre-trained VGG16 model on the ImageNet dataset and the configuration of learning rates is the same as model A. For loss weights in the coarse-grained branches training step, we set them all the same.

The results are shown in Table II. The baseline model A gets an accuracy of 82.94% and the B-CNN model achieves 84.70%. Our VT-CNN model beats the B-CNN model by an accuracy of 85.07%. The accuracy in Base B model is 87.15% while the B-CNN model reaches 88.23%. Our VT-CNN model achieves 89.51%. The improvement is obvious which indicates that the performance of our VT-CNN models is better than original CNN models and the B-CNN models on CIFAR-10 dataset.

### C. CIFAR-100

In this section, we evaluate our VT-CNN model on CIFAR-100 dataset. The experiment is consist of two parts. The one is the comparison with VT-CNN models, baseline models of 3 original CNN models and B-CNN models based on these baseline models. The other is the comparison among VT-CNN models constructed on different visual tree structures.

First, we introduce 3 original CNN models which are AlexNet, VGG16 and ResNet-56. The configurations for the AlexNet model and the VGG16 model on CIFAR-100 dataset are the same as the Base A model and the Base B model in Section IV-B. The ResNet-56 [17] is a residual learning network of depth 56 using residual blocks of 2 convolutional layers.

We construct VT-CNN models based on these baseline models. Their branch architecture configurations are similar with the configuration in Section IV-B because the main idea of the VT-CNN model is that the branches should connect to different positions on the base layers. There is a little different that our CVT on CIFAR-100 dataset has 5 layers so there are 4 branches in VT-CNN models.

### TABLE I: The entire architecture for each VT-CNN model.

| Layers of Base A | Layers of Base B |
|------------------|------------------|
| (Conv3-98)-MaxPool | (Conv3-64)$_{x2}$-MaxPool |
| (Conv3-256)-MaxPool | (Conv3-128)$_{x2}$-MaxPool |
| (Conv3-384) | (Conv3-256)$_{x3}$-MaxPool |
| conv-3 Flatten | (Conv3-256)$_{x2}$ |
| FC-256 | FC-512 |
| FC-256 | FC-512 |
| FC-C$_{A1}$ | FC-C$_{B1}$ |
| (Conv3-384) | (Conv3-512)$_{x3}$-MaxPool |
| conv-4 Flatten | (Conv3-512)$_{x2}$ |
| (Conv3-256)$_{x2}$ | (Conv3-512)$_{x2}$ |
| FC-512 | FC-1024 |
| FC-512 | FC-1024 |
| FC-C$_{A2}$ | FC-C$_{B2}$ |
| (Conv3-256)-MaxPool | (Conv3-512)$_{x3}$-MaxPool |
| conv-5 Flatten | Probabilistic averaging layer |

### TABLE II: Performance of each model on CIFAR-10 test set.

| Models     | Top-1 Accuracy |
|------------|----------------|
| Base A     | 82.94%         |
| B-CNN A    | 84.70%         |
| VT-CNN A   | 85.07%         |
| Base B     | 87.15%         |
| B-CNN B    | 88.23%         |
| VT-CNN B   | 89.51%         |

### TABLE III: Performance of each model on CIFAR-100 test set.

| Models     | Top-1 Accuracy |
|------------|----------------|
| AlexNet A  | 57.37%         |
| B-CNN A    | 58.27%         |
| VT-CNN A   | 58.73%         |
| VGG16 B    | 71.15%         |
| B-CNN B    | 71.23%         |
| VT-CNN B   | 72.04%         |
| ResNet-56 C| 73.49%         |
| B-CNN C    | 73.86%         |
| VT-CNN C   | 74.13%         |
These 3 baseline models and their derived B-CNN and VT-CNN models are trained in 80 epochs and using the different learning rates at different epochs. The learning rates are initialized to be 0.001 and decrease to 0.0002 after 55 epochs and 0.00005 after 70 epochs. The complete experiment results are given in Table [IV]. In every case, our VT-CNN model achieves highest accuracy than the corresponding base model and the derived B-CNN model. In the case of AlexNet, the relative improvement is 1.36% compared with the base model and 0.46% compared with the B-CNN model. The VGG16 model is used as base model to train the VT-CNN model. The VGG16 model gives 71.15% and the derived B-CNN model gives 71.23%, whereas we achieve 72.04%. Finally, we consider about the state-of-the-art technique ResNet as the baseline model and use the ResNet-56 model. The accuracy of 74.13% obtained by our VT-CNN model built from the ResNet-56 model is the best result in this experiment while the ResNet-56 model reaches 73.49% and the B-CNN model achieves 73.86%. We find that our VT-CNN model achieves the best performance in the classification task on the CIFAR-100 dataset compared with the original CNN models and their derived B-CNN models.

Then we do experiment on comparison of VT-CNN models constructed on different visual tree structures. The following competing tree structures are chosen for comparison: Semantic Ontology [8], Label Tree [4], Visual Tree [5] and the state-of-the-art technique Enhanced Visual Tree [13]. The classification performance of all the VT-CNN based on these structures are reported in Table [IV].

**TABLE IV: Results on VT-CNN with different tree structures.**

| Tree Structure in VT-CNN | Accuracy  |
|--------------------------|-----------|
| Semantic Ontology        | 57.18%    |
| Label Tree               | 64.39%    |
| Visual Tree              | 69.48%    |
| Enhanced Visual Tree     | 72.14%    |
| Confusion Visual Tree    | 74.13%    |

Observing Table [IV], we find the performance of Semantic Ontology is the worst because its tree structure is constructed based on semantic space and the image classification process based on feature space [3]. For another four methods based on feature space, the performance of the Label Tree is worse because of using OvR classifier to construct its tree structure, which is limited to sample imbalance and the performance of classifier. As for the Visual Tree, it uses the average features extracted directly from the dataset. The Enhanced Visual Tree adopts the spectral clustering method that better reflects the diversity of categories, so its performance is better than the Visual Tree [13]. Our CVT constructs the tree structure based on the confusion of the neural network, which makes sibling nodes as close as possible to the parent node as far as possible. So the structure of the CVT is more proper and we obtain a significant improvement over the Visual Tree and the Enhanced Visual Tree by 4.65% and 1.99%.

**V. CONCLUSION**

In this paper, we propose a Visual Tree Convolution Neural Network (VT-CNN) which connects the original CNN models with the visual tree. Compared with original CNN models, VT-CNN models can utilize the prior information in coarse-grained category classification to improve the performance of the final fine-grained category classification. We also introduce a method to construct a Confusion Visual Tree (CVT) which provides a more reasonable tree structure for the VT-CNN models. The experiment results confirm the benefits of our VT-CNN model with CVT over the original CNN model. For further work the improvement on the final fine-grained classification layers, such as splitting the all-category FC-softmax layer to several fine-grained category sets FC-softmax layers, should be investigated.

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