Improve CNN Classifications by Ensemble Learning, Stacking in CIFAR10 Dataset

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1 Introduction

Image classification is the task of classifying an image into a class category. Many traditional models have been proposed to classify images such as KNN, SVM and Neural Network. But the result of those traditional models can't reach our goal and it is too hard to implement in real situation. A new model was proposed by Alex Krizhevsky at all at the time of 2012. This model is called CNN.

In this project, to explore a better architecture of CNN model and purse a breakthrough of the accuracy of image classification, we will train two special CNN models based on the data set CIFAR-10 and implement the Ensemble Learning Stacking to improve results. Stacking is an ensemble learning technique that combines multiple classification or regression models via a meta-classifier or a meta-regressor. The final accuracy of this project in this data set is 93.51%.

2 Methodology

2.1 CIFAR-10 Data Set

The CIFAR-10 data set consists of 60000 32×32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images. The data set is divided into training batches and one test batch. As the distinguish of the distribution of training set and testing set will have a huge impact on the performance of the CNN model, we will let the distribution of training data set is the same as that of testing data set in the CIFAR-10. For details, the test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order. The training batches contain exactly 5000 images from each class. The classes are completely mutually exclusive.

2.2 Mobile Net V2 [1]

Mobile Net V2 is one of the CNN model used for mobile or the resource constrained environments. One of its special features is that it has less parameters while the performance

of this net in some data sets is excellent. This Net is established on the Inverted Residual Block(Figure 2) and the Inverted Residual Block is improved from Depthwise Separable Convolutions(Figure 3).

The reason why we choose this net is that we appreciate the efficiency and the high performance of this net in some cases.

2.2.1 Tiny Modify For Mobile Net V2

1. Replace the Batch Normalization[2] to Group Normalization[3] after the depthwise convolution. The reason is that depthwise convolution performs lightweight filtering by applying a single convolutional filter for per input channel. The different convolutional filters will learn different information from per input channels. If we use Batch Normalization to the output of depthwise convolution, we would have a wrong estimator of the mean μ and variance σ^2 of each pixel in the output. This is because each output channel of depthwise convolution comes from different convolutional filters. This may indicate that the distribution of each output channel is different.

2. From the paper [4] we can know that the performance of one net is highly relevant to the resolution of input images, the depth of the net and the channels number of each layers. Inspired by this paper, we extend our Mobile Net V2 model in to $Original\_Depth \times 2$, $Original\_Channels \times 2$ and $Original\_Resolutions \times 1$.

2.3 ResNeSt Net[5]

ResNeSt Net is a modified convolution net from the ResNet[6]. In the paper, the authors added a Split-Attention block(Figure 4) that enables attention to across feature-map groups. The Split-Attention block is like the upgrade of the SE block[7] but enhances much non-linear transformation ability compared with it. By stacking these Split-Attention blocks in ResNet-style, the authors obtain a new ResNet variant which we call ResNeSt(Figure 5).

The reason why we choose this model is that it achieves the best performance in the classification on the Image-Net data set and the best mAP of the objection detection on the COCO data set. It is the SOTA model at present.

2.3.1 Tiny Modify For ResNeSt Net

1. Replace the Batch Normalization[2] to Group Normalization[3] in the split convolution blocks. The intuition is as same as the Mobile Net V2.

2. Inspired by this paper [4], we extend our ResNeSt Net (50 Layers) model in to $Original\_Depth \times 2$, $Original\_Channels \times 1$ and $Original\_Resolutions \times 1$.

2.4 Ensemble Learning, Stacking

In the algorithm Stacking, the base level models (Mobile Net V2, ResNeSt Net) are trained based on a complete training set, then we will build a meta-model which is trained on the outputs of the base level model as features to enhance the accuracy.

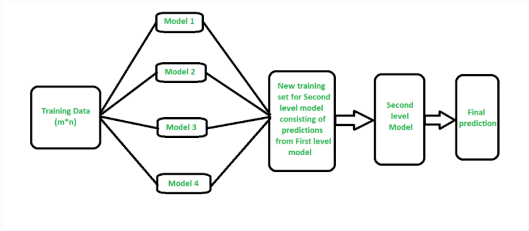

Figure 1: *The work flow of the algorithm Stacking.*

The meta-model we used is a three layers neural network without any activation. It just makes linear transformation with the output features of Mobile Net V2 and ResNeSt Net. To amplify the effect of correct feature (i.e. The correct prediction output of one of net), we used 1024 hidden units for the output of Mobile Net V2 and ResNeSt Net. In the next step, we added the two linear transformed tensors and the predictive output of meta-model is the linear transformation of the added tensors.

2.5 Regularization

Regularization is also a key to deciding if we can train a excellent CNN model. The regular regularization method like dropout[8] is not suitable for CNN model in that dropout is suitable for fully connection layers. However, CNN is a partial connection layer. To solve this problem, we used Drop Connection [9] method. This regularization method can open or close one block with the *Bernoulli* distribution.

3 Implementation Details

3.1 Training Implementation

To fully train the Mobile Net V2 and ResNeSt Net, we conducted 350 epochs for each net. The learning rate is also a key to train the net successfully. The learning rate schedule is: 0.1 for epoch $[0 \sim 150]$, 0.01 for epoch $[151 \sim 250]$ and 0.001 for epoch $[251 \sim 350]$. The mini-batch size is 128 and the normalization layers are added between each convolution layers and the activation layers. Because of the same number of images in each class, we used the same weight Cross Entropy Loss. To enhance the performance of each net, we used data augmentation for CIFAR-10 data set. The methods we used are random crop and random horizontal flip. To guarantee fast speed of convergence and higher precision of the final result, we used Adam Bound [10] optimizer for optimizing. The feature of this optimizer is that it performs like Adam in the early stage of training and converts into SGD with momentum gradually, which gives itself a fast speed of convergence in the initial state and high precision result at the end of training.

To train meta-model, we used Cross Entropy Loss and SGD with momentum optimizer. The learning rate in this training procedure is a constant which is 1×10^{-6}. To fully train this meta-model, the epoch we set is 300.

All of those training processing is based on the GPU, GTX-1080Ti.

3.2 Regularization Implementation

In Mobile Net V2, the Drop Connection method is conducted after Inverted Residual Block. In ResNeSt Net, this method is behind the ResNeSt block. The probability set for Mobile Net V2 is 0.45 and set 0.47 for ResNeSt Net. This is because ResNeSt is more complicate than Mobile Net V2. We used the dropout method at the last fully connection layer in those two CNN models. The probability for dropout is 0.75 and 0.77 for Mobile Net V2 and ResNeSt Net.

Beside, we also apply the weight decay regularization. The set of parameters is 5×10^{-4}, 5.1×10^{-4} and 1.5×10^{-6} for Mobile Net V2, ResNeSt Net and meta-model respectively.

4 Results

The result of accuracy of those models are shown below. It proves our assumption that the distribution of training data set is as same as the distribution of testing data set. This is because we get a 93.51% accuracy in the testing data set. If the distribution of training and testing are different, our model is hard to generalize performance from training data set to testing data set to obtain a high accuracy.

	Accuracy
Mobile Net V2	92.58%
ResNeSt Net	90.51%
Meta Model	93.51%

Table 1: *The accuracy of each trained models.*

From the table 1, we can know that the accuracy of complicate ResNeSt Net is lower than the simple Mobile Net V2. In general, a more complicate model tends to have more non-linear ability leading to a greater result. However, it does not work in this case. This may account for the resolution of image in this CIFAR-10 data set. In face of the low resolution image, a complicate CNN model has a larger tendency to overfit than a simple CNN model. If we train a data set like Image Net with huge resolution, the ResNeSt may have a better performance than the Mobile Net V2.

Besides, we can also see that the accuracy of Meta model is higher than any single CNN model. This indicates that Ensemble Learning, Stacking is useful when we have different types of models for one task. This algorithm will raise $1\% \sim 2\%$ of the accuracy. In the future, if we face a problem which is hard to solve by one of machine leraning models, we can use Ensemble Learning to improve our model.

References

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Supplementary Material

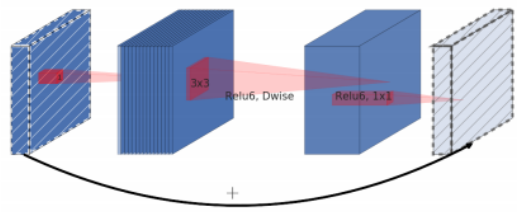

Figure 2: *Inverted residual block*

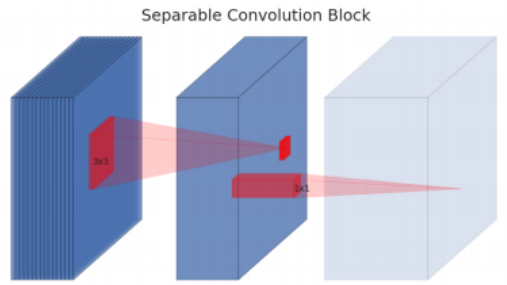

Figure 3: *Separable Convolution Block, the first stage is Depthwise Separable Convolutions*

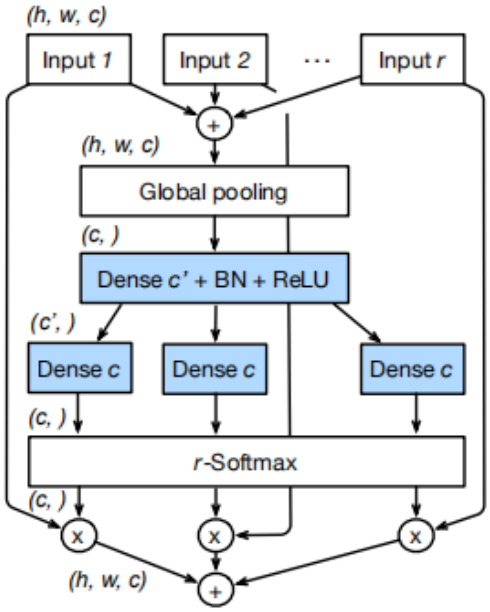

Figure 4: *Architecture of Split-Attention Block*

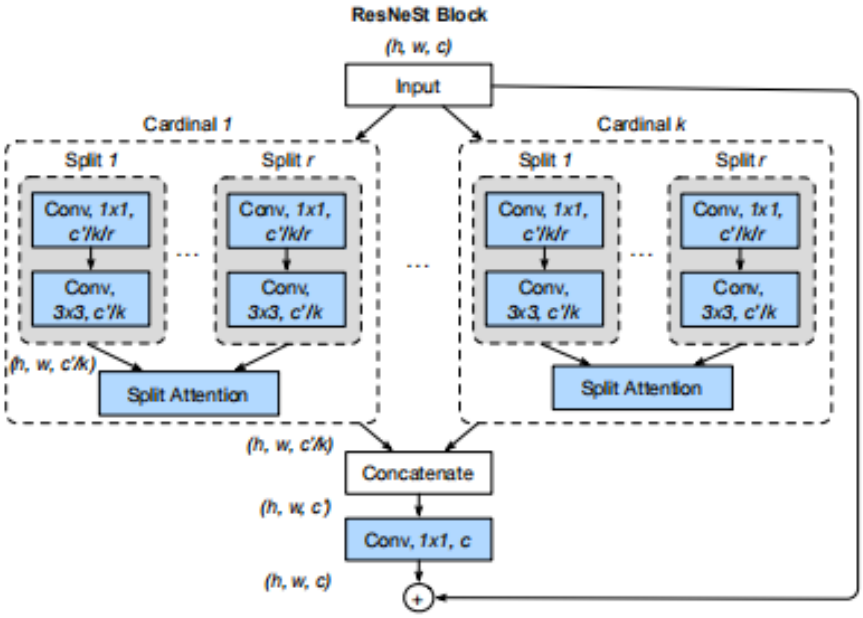

Figure 5: *Architecture of ResNeSt Block*