A-MnasNet: Augmented MnasNet for Computer Vision

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Abstract—Convolutional Neural Networks (CNNs) play an essential role in Deep Learning. They are extensively used in Computer Vision. They are complicated but very effective in extracting features from an image or a video stream. After AlexNet [5] won the ILSVRC [8] in 2012, there was a drastic increase in research related with CNNs. Many state-of-the-art architectures like VGG Net [12], GoogleNet [13], ResNet [18], Inception-v4 [14], Inception-Resnet-v2 [14], ShuffleNet [23], Xception [24], MobileNet [6], MobileNetV2 [7], SqueezeNet [16], SqueezeNext [17] and many more were introduced. The trend behind the research depicts an increase in the number of layers of CNN to make them more efficient but with that the size of the model increased as well. This problem was fixed with the advent of new algorithms which resulted in a decrease in model size. As a result, today we have CNN models which are implemented on mobile devices. These mobile models are small and fast which in turn reduce the computational cost of the embedded system. This paper resembles similar idea, it proposes a new model Augmented MnasNet (A-MnasNet) which has been derived from MnasNet [1]. The model is trained with CIFAR-10 [4] dataset and has a validation accuracy of 96.89% and a model size of 11.6 MB. It outperforms its baseline architecture MnasNet which has a validation accuracy of 80.8% and a model size of 12.7 MB when trained with CIFAR-10.

Index Terms—Convolutional Neural Networks (CNNs), Computer Vision, A-MnasNet, CIFAR-10, MnasNet.

I. INTRODUCTION

Convolutional Neural Networks have become an integral part of Computer Vision. They are extensively used for Computer Vision applications like Image Classification [19], Object Detection [21] and Semantic Segmentation [20]. As these models become deeper, they need more computation and as a result they become slower. This makes it difficult to deploy them on resource-constrained platforms.

Mobile devices have limited resources so the prime focus of researchers has been on designing compact models with a fair trade-off between accuracy and computational cost. A new class of CNN model was proposed in May 2019 by Google Brain and Google Inc known as MnasNet. They introduced a neural architecture search approach which optimized accuracy and latency on mobile devices. It outperforms other novel architectures like MobileNetV2, NASNet [30] and ResNet-50 [12] in terms of speed and accuracy.

II. PRIOR WORK

The research has been mainly focused on improving resource efficiency of CNN models. Weight initialization, learning rates, activation functions, network topology, batches and epochs, regularization and optimization are different parameters that affect the efficiency of model. In this paper, first baseline architecture and then the new architecture with pro-

Fig. 1. MnasNet architecture

posed changes have been discussed.

A. MnasNet Architecture

In this paper, they have introduced a neural architecture search approach which optimized accuracy and latency on mobile devices using reinforcement learning. By using their automated approach, they propose various architectures called MnasNet-A1, MnasNet-A2 and MnasNet-A3. They show that diversity of layers in such resource-constrained models yield better trade-offs between accuracy and latency of the model. They have shown that their architecture outperforms other models like MobileNetV1, SqueezeNext, ShuffleNet, MobileNetV2, NASNet and many other models.

As shown in Figure 1, MnasNet uses Convolution Ops, depthwise separable convolution, mobile inverted bottleneck layers to extract features. It uses RMSProp optimizer [31], Batch Normalization [27] and Dropout regularization [32]. Table I shows the MnasNet architecture which is trained with CIFAR-10 dataset.

MnasNet Architecture					
Layers	Convolutions	t	c	n	s
$32^2 \times 3$	Conv2d 3×3	-	32	1	1
$112^2 \times 32$	SepConv 3×3	1	16	1	2
$112^2 \times 16$	MBConv3 3×3	3	24	3	2
$56^2 \times 24$	MBConv3 5×5	3	40	3	2
$28^2 \times 40$	MBConv6 5×5	6	80	3	2
$14^2 \times 80$	MBConv6 3×3	6	96	2	1
$14^2 \times 96$	MBConv6 5×5	6	192	4	1
$7^2 \times 192$	MBConv6 3×3	6	320	1	1
$7^2 \times 320$	FC, Pooling			10	

TABLE I

WHERE T: EXPANSION FACTOR, C: NUMBER OF OUTPUT CHANNELS, N: NUMBER OF BLOCKS AND S: STRIDE

III. A-MNASNET ARCHITECTURE

This section will explain the proposed architecture, A-MnasNet, and the modifications made to the baseline architecture MnasNet.

A. Convolution Layers

MnasNet uses Depthwise Separable Convolutions. It has two layers of convolution. First, a 3×3 or 5×5 depthwise convolution layer. Second, a 1×1 pointwise convolution layer. The spatial dimensions along this convolution blocks remain constant. To increase the accuracy of the model, the convolutions must extract features in an efficient way. The channel expansion-contraction transformation throughout the architecture results in very wide feature maps in the middle of the building block. This increases the computational burden of such layers.

In order to reduce these computations, new convolutional layers were introduced in the model which are known as Harmonious Bottleneck Layers [2]. These layers focus on the spatial transformations along with channel transformations. They change the spatial feature scale along composite layers of the network. This strikes an improved balance between

A-MnasNet Architecture					
Layers	Convolutions	t	c	n	s
$32^2 \times 3$	Conv2d 3×3	-	32	1	1
$112^2 \times 32$	SepConv 3×3	1	16	1	2
$112^2 \times 16$	MBConv3 3×3	3	24	3	2
$112^2 \times 4$	Harmonious Bottleneck	2	36	1	1
$56^2 \times 36$	MBConv3 5×5	3	40	3	2
$112^2 \times 40$	Harmonious Bottleneck	2	72	1	2
$28^2 \times 72$	MBConv6 5×5	6	80	3	2
$112^2 \times 80$	Harmonious Bottleneck	2	96	4	2
$14^2 \times 96$	MBConv6 3×3	6	96	2	1
$14^2 \times 96$	MBConv6 5×5	6	192	4	1
$7^2 \times 192$	MBConv6 3×3	6	320	1	1
$7^2 \times 320$	FC, Pooling			10	

TABLE II

WHERE T: EXPANSION FACTOR, C: NUMBER OF OUTPUT CHANNELS, N: NUMBER OF BLOCKS AND S: STRIDE

Fig. 2. Comparison of Depthwise Separable Convolution Layer and Harmonious Bottleneck Layer. [2]

the representation capability and efficiency by considering the spatial transformation.

As shown in Figure 2, there is contraction-expansion of spatial dimensions and expansion-contraction of channel dimensions in the harmonious bottleneck layer. First, the channel dimensions are kept constant and features are extracted from the spatial dimensions. Second, the spatial dimensions are kept constant and features are extracted from channel dimensions. This makes the convolution layer more efficient and increases the accuracy of the model.

Figure 2 shows the comparison of depthwise separable convolutional block and harmonious bottleneck layer. The spatial size of input/output feature maps is $(H \times W)$, $C1/C2$ are input/output feature channels, $(K \times K)$ is the kernel size and s denotes stride.

The total cost of depthwise separable convolution is

$$(H \times W \times C1 \times K \times K) + (H \times W \times C1 \times C2) \quad (1)$$

The total cost of harmonious bottleneck layer is

$$B/s^2 + (H/s \times W/s \times C1 + H \times W \times C2) \times K^2 \quad (2)$$

where, B is the computational cost of the blocks inserted between the spatial contraction and expansion operations. It is evident that by squeezing the channel expansion-contraction component and using a pair of spatial transformations yields a

slimmed spatial size of wide feature maps in each stage which reduces the computational cost.

In this paper, three harmonious bottleneck layers were added to the MnasNet architecture to increase the accuracy. The model is described in table II. After adding these layers, the accuracy of the model increased by 12.17% whereas the model size decreased from 12.7 MB to 11.6 MB. The comparison is shown in Table III.

B. Learning Rate Annealing or Scheduling

While training a network, different learning rates are used to increase its accuracy. According to a pre-defined schedule, the learning rate is reduced while training the model. Some techniques like step decay, time decay, exponential decay and cosine annealing are very famous. Figure 3 illustrates step decay based learning rate performs better than other learning rate schedule methods. Therefore, this method is used for training A-MnasNet.

Fig. 3. Comparison of different LR scheduling methods. [33]

C. Optimization

Different optimization techniques can be used to optimize the performance of the network. Adaptive Learning Rate Method (Adadelta) [31], Adaptive Gradient Learning Algorithm (Adagrad) [31], Adaptive Moment Estimation technique (Adam) [31], Stochastic Gradient Descent method [31] and many more optimizers are widely used. RMSprop was used to optimize the MnasNet architecture. In this paper, SGD was implemented with varying values of learning rates and momentum=0.9 for better optimization.

D. Data Augmentation

AutoAugment [3] was used for data augmentation. AutoAugment learns the best augmentation policies for a given dataset with the help of Reinforcement Learning (RL). A policy consists of 5 sub-policies and each sub-policy applies 2 image operations in sequence. Each of those image operations has two parameters: The probability of applying it and the magnitude of the operation (e.g. rotate 20 degrees in 65% of

cases). There is a controller that decides the best data augmentation policy at that instant and tests the generalization ability of that policy by running a child model experiment on a small subset of a particular dataset. After the child experiment is finished the controller is updated with the validation accuracy as the reward signal, using a policy gradient method called Proximal Policy Optimization algorithm (PPO). In this paper, AutoAugment is used on CIFAR-10 dataset. The accuracy of A-MnasNet was 92.97% but after using AutoAugment the accuracy increased to 96.89%.

IV. HARDWARE AND SOFTWARE

- Intel i9 9th generation processor with 32 GB RAM.
- Aorus Geforce RTX 2080Ti GPU
- Python version 3.6.7
- Pytorch version 1.0
- Spyder version 3.6
- Livelossplot (Loss and accuracy visualization).

V. RESULTS

After making the aforementioned modifications to the baseline architecture, the model was trained with CIFAR-10 dataset on Aorus Geforce RTX 2080Ti GPU using PyTorch framework for 200 epochs. The data was divided into batch size of 128 for training set and batch size of 64 for validation set.

Figure 4 and figure 5 shows the plots of log loss and accuracy of their respective models. The graphs were plotted using livelossplot visualization library.

The trade-off between model size and accuracy is shown in table III

Fig. 4. MnasNet (Baseline Architecture)

Fig. 5. A-MnasNet (Proposed Architecture)

Table IV shows the results obtained by scaling the model with different values of width multiplier.

Comparison of models		
Architecture	Model Accuracy	Model size (in MB)
MnasNet	80.8%	12.7
A-MnasNet	96.89%	11.6

TABLE III
COMPARISON WITH BASELINE ARCHITECTURE

Scaling A-MnasNet with width multiplier		
Width Multiplier	Model Accuracy	Model size (in MB)
1.4	97.16%	22
1.0	96.89%	11.6
0.75	96.64%	6.8
0.5	95.74%	3.3
0.35	93.36%	1.8

TABLE IV
VARYING MODEL SIZE BY WIDTH MULTIPLIER

VI. CONCLUSION

In this paper, A-MnasNet, a new architecture is introduced by modifying MnasNet, its baseline architecture. The prime goal of this paper is to make the model more efficient in terms of accuracy. The accuracy of A-MnasNet is 96.89% with a size of 11.6 MB. It outperforms its baseline architecture MnasNet which has an accuracy of 80.8% and model size of 12.6 MB. Three new layers were added to the baseline architecture. These layers are called Harmonious Bottleneck layers. AutoAugment was used to further increase the accuracy of the model. This model can be implemented on mobile devices and other embedded systems. It can be used for applications like image classification, object detection and semantic segmentation.

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