EffNet: AN EFFICIENT STRUCTURE FOR CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT
With the ever increasing application of Convolutional Neural Networks to consumer products the need emerges for models which can efficiently run on embedded, mobile hardware. Slimmer models have therefore become a hot research topic with multiple different approaches which vary from binary networks to revised convolution layers. We offer our contribution to the latter and propose a novel convolution block which significantly reduces the computational burden while surpassing the current state-of-the-art. Our model, dubbed EffNet, is optimised for models which are slim to begin with and is created to tackle issues in existing models such as MobileNet and ShuffleNet.

Index Terms — convolutional neural networks, computational efficiency, real-time inference

1. INTRODUCTION
With recent industrial recognition of the benefits of Artificial Neural Networks to product capabilities, the demand emerges for efficient algorithms to run in real-time on cost-effective hardware. This contradicts, in a way, the now parallel university research. While the latter enjoys a relative freedom in terms of execution cycles and hardware, the former is subjected to market forces and product requirements.

Over the years multiple papers proposed different approaches for tackling the problem of real-time inference on a small hardware. One common method is the pruning of trained networks [1], [2], [3]. Another is the fix-point conversion of 32bit networks to as far as binary models [4]. A more recent approach concentrates on the interconnectivity of the neurons and the very nature of the vanilla convolution layers.

A vanilla convolution layer consists, in its core, of a four-dimensional tensor which is swept over an input signal in the following format \([\text{rows, columns, channels in, channels out}]\), resulting in a quadruple-component multiplication. This means that the computational cost scales by a four-fold factor.

As \(3 \times 3\) convolutions are now a standard, they become a natural candidate for optimisation. Papers as [5] (MobileNet) and [6] (ShuffleNet) set to solve this issue by separating the computations along the different dimensions. Yet in their methods they leave two large issues unaddressed. First, both papers report taking large networks and making them smaller and more efficient. When applying their models to slimmer networks the results start to diverge. Second, both proposed models create an aggressive bottleneck [7] for data flow in the network. This kind of a bottleneck might prove insignificant in models of high redundancy yet, as our experiments show, it has a destructive effect on smaller models.

We therefore propose an alternative constellation which retains most of the proportional decrease in computations while having little to no affect on the accuracies. We achieve this improvement by optimising data flow through the network and neglecting practices which prove harmful in this unique domain.

2. RELATED WORK
Much of the work in the field focuses on hyper-parameter optimisation. Algorithms from this class are rather general both in terms of target algorithm and optimisation objective. [8] proposed a general Bayesian optimisation framework for black-box algorithms as CNNs \(^1\) and SVMs \(^2\) by maximising the probability of increasing the model’s accuracy. This could be combined with multi-objective optimisation as in [9], to also optimise the computational complexity. These methods mostly work well when initialised properly and many of them are limited in their search space [10]. Using reinforcement learning, [11] trained an LSTM \(^3\) to optimise hyper-parameters for improved accuracy and speed. This along with recent evolutionary methods [13] exhibits less limitations on the search space but complicates the development by deploying additional modules.

An additional approach resolves to decreasing the size of large models in a post-processing manner. Papers such as [1], [2] and [3] proposed pruning algorithms with a minimal cost to accuracies. However pruning leads to several issues. The pipeline itself requires an additional phase with dedicated hyper-parameters which require optimisation. Furthermore,
the network’s architecture is changed, the models require an additional fine-tuning step.

A further method for compression through post-processing is the fix-point quantisation of models to smaller primitives than the common 32bit floats [14] [15], [16] and the binary networks of [4]. Quantised models, although much faster, consistently show decreased accuracies compared to their baselines and are thus less appealing.

Last, similar to this work, papers as [17], [5] and [6] revisited the very nature of the common convolution operator. This involves the dimension-wise separation of the convolution operator, as discussed in [18]. Here, the original operation is approximated using significantly less FLOPs. [7] separated the $3 \times 3$ kernels into two consecutive kernels of shapes $3 \times 1$ and $1 \times 3$. The MobileNet model [5] took a step further and separated the channel-wise from the spatial convolution which is also only applied depthwise, see Figure 1b. By doing so a significant reduction in FLOPs was achieved while the majority of computations was shifted to the point-wise layers. Finally, the ShuffleNet model [6] addressed the stowage of FLOPs in the point-wise layers by dividing them into groups in a similar way to [19]. This lead to a drastic reduction in FLOPs with a rather small toll on the accuracies, see Figure 1 in [6] and Figure 1c.

The diversity of methods shows that there are multiple ways to successfully compress a CNN. Yet most methods assume a large development model which is adjusted for efficiency. They thus commonly seem to reach their limits when applied to networks which are slim to begin with. As many embedded systems have a limited specification, models are normally designed within these limitations rather than just optimising a large network. In such environments the limitations of [5] and [6] become clearer thus laying the base for our EffNet model which shows the same capacity even when applied to shallow and narrow models.

Finally notice that the methods above are not mutually exclusive. For example, our model could also be converted to fixed-point, pruned and optimised for best set of hyper-parameters.

3. BUILDING BLOCKS FOR INCREASED EFFICIENCY

This section discusses the most common practices for increasing efficiency. The presented results assisted with identifying weaknesses in previous techniques and constructing a suitable solution in the form of a unified EffNet block. For practical reasons we avoid going into details regarding the exact settings of the following experiments. Instead we discuss their results and show their effect as a whole in section 5.

The combination of multiple tasks, competitive costs and interactive run-times puts strict limitations on possible model sizes for industrial applications. These requirements in fact often lead to the usage of more classical computer vision algorithms which are optimised to run a specific task extremely quick, e.g. [20]. Additionally, regulatory limitations often prohibit a one network solution as they require backup systems and highly interpretable decision making processes. Reducing the computational cost of all small classifiers in a project would thus allow either the redistribution of computational power to more critical places or enable deeper and wider models with a larger capacity.

Exploring the limitations of previous work revealed that the smaller the model is, the more accuracy it loses when converted to MobileNet or to ShuffleNet, see section 5. Analysing the nature of these suggested modifications we came across several issues.

The Bottleneck Structure The bottleneck structure as discussed in [21] applies a reduction factor of eight to the number of input channels in a block, comparing to the number of output channels. A ShuffleNet block uses a reduction factor of four [6]. Yet narrow layers do not tend to have enough channels to enable such a drastic reduction. In all of our experiments we witnessed a loss in accuracy comparing to more moderate reduction and we therefore propose to use a bottleneck factor of two.

Separable Convolutions Proposed by [7] and used neither by ShuffleNet nor by MobileNet, we revisit the idea of consecutive separable spatial convolutions, i.e. using $3 \times 1$ and $1 \times 3$ layers instead of a single $3 \times 3$ layer. Separating the spatial convolution might only make a minor difference in terms of FLOPs but we could not find any reason not to use it.

Strides and Pooling Both MobileNet and ShuffleNet models choose to apply a stride of two to the depthwise spatial convolution layer in their blocks. Our experiments show two issues with this practice. First, we repeatedly witnessed a decrease in accuracy comparing to max-pooling. This was in a way expected as strided convolution is prone to aliasing.

Additionally, applying max-pooling to the spatial convolution layer does not allow the network to properly encode the
Table 1: Data flow analysis of selected models. One could intuitively understand how an aggressive data compression in early stages would harm accuracies. Compression factors of 4 or more are marked in red. gc4 means convolution in 4 groups. Best seen in colour.

| Layer Floats Out | Layer Floats Out | Layer Floats Out | Layer Floats Out |
|------------------|------------------|------------------|------------------|
| 3x3x64 + mp 16384 | 3x3x64 + mp 16384 | 3x3x64 + mp 16384 | 1x1x32 32768 |
| 3x3x128 + mp 8192 | dw 3x3 + stride 4096 gc4 1x1x32 | 8192 dw 3x3 + stride 4096 gc4 1x1x128 | 8192 |
| 3x3x256 + mp 4096 | dw 3x3 + stride 4096 gc4 1x1x64 | 4096 dw 3x3 + stride 4096 gc4 1x1x256 | 4096 |
| Fully Connected 10 | Fully Connected 10 | Fully Connected 10 | Fully Connected 10 |

4. THE EffNet MODEL

4.1. Data Compression

Upon analysing the effects of the various methods discussed in section 3, we established that small networks are very sensitive to data compression. Throughout the experiments, each method which led to a larger bottleneck in data flow had also resulted in decreased accuracies. For a better understanding of the data flow concept Table 1 lists the dimensionality of an input through the different stages of our Cifar 10 [23] network comparison.

4.2. The EffNet Blocks

We propose an efficient network structure which at the same time solves the issue of data compression and implements the insights from section 3. We design this block as a general construction to seamlessly replace the vanilla convolutional layers in, but not limited to, slim networks.

We start by, in a similar manner to [7], splitting the \( 3 \times 3 \) depthwise convolution to two linear layers. This allows us to pool after the first spatial layer, thus saving computations in the second layer.

We then split the subsampling along the spatial dimensions. As seen in Table 1 and in Figure 1 we apply a \( 1 \times 2 \) max pooling kernel after the first depthwise convolution. For the second subsampling we choose to replace the common pointwise convolution with \( 2 \times 1 \) kernels and a corresponding stride. This practically has the same amount of FLOPs yet leads to slightly higher accuracies.

Following the preliminary experiments in section 3, we decide to relax the bottleneck factor for the first pointwise convolution. Instead of using a fourth of the output channels, we recognise a factor of 0.5, with a minimal channel amount of 6, as preferable.
5. EXPERIMENTS

This section covers the evaluation of our model. We select datasets which comply with our general settings; a small number of classes and a relatively small input resolution. We then do a quick manual search for probable hyper-parameters for the baseline which fulfill the requirements; two to three hidden layers and small number of channels. The other architectures then simply replace the convolutional layers without changing the hyper-parameters.

Architectures were executed at least five times to cancel out the effects of random initialisation.

To concentrate the experiments on our model, we did not apply any sort of data augmentation or pre-training on additional data as proposed by [24]. Furthermore, we did not use hyper-parameter optimisation as our goal is to replace the convolution layers in every given network with the EffNet blocks. This makes our model simpler to use as it allows developers to not worry about the implications of the swap to EffNet blocks.

We used Tensorflow [25] for all experiments. Networks were trained using the Adam optimiser [26] with a learning rate of 0.001 and $\beta_1 = 0.75$.

As an additional experiment, we evaluate a larger EffNet model with roughly the same amount of FLOPs as the baseline. This is dubbed large in the following results.

| Mean Accuracy | Mil. FLOPs | Factor |
|---------------|------------|--------|
| Baseline      | 79.5%      | 39.2   | 1.00 |
| MobileNet     | 77.7%      | 4.7    | 0.12 |
| ShuffleNet    | 75.6%      | 4.1    | 0.11 |
| EffNet (ours) | 82.0%      | 7.2    | 0.18 |
| EffNet large  | 87.1%      | 43.7   | 1.11 |

5.1. Cifar 10

Being a fundamental simple datasets in computer vision, Cifar10 [23] is a good example of the sort of tasks we aim to improve on. Its images are small and represent a limited number of classes. We achieve a significant improvement over MobileNet, ShuffleNet and even the baseline while still requiring $\sim 7$ times less FLOPs than the baseline (see Table 2). We relate this improvement to the additional depth of the network meaning that the EffNet blocks simulate a larger, deeper network which does not underfit as much as the other models.

5.2. Street View House Numbers

Similar to Cifar10, the SVHN benchmark [27] is also a common dataset for evaluation of simple networks. The data consists of $32 \times 32$ pixel patches centred around a digit with a corresponding label. Table 3 shows the results of this experiment which favour our EffNet model both in terms of accuracy and FLOPs.

| Mean Accuracy | kFLOPs | Factor |
|---------------|--------|--------|
| Baseline      | 91.08% | 3,393.1| 1.00 |
| MobileNet     | 85.64% | 1,036.2| 0.31 |
| ShuffleNet    | 82.73% | 958.6  | 0.28 |
| EffNet (ours) | 88.51% | 756.6  | 0.22 |
| EffNet large  | 91.26% | 3,458.2| 1.02 |

5.3. German Traffic Sign Recognition Benchmark

A slightly older dataset which is nevertheless very relevant in most current driver assistance applications is the GTSRB dataset [28]. With over 50,000 images and some 43 classes it presents a rather small task with a large variation in data and is thus an interesting benchmark. As even small networks started overfitting very quickly on this data, we resize the input images to $32 \times 32$ and use a dropout [29] layer with drop-probability of 50% before the output layer. Results are shown in Table 4 and also favour our EffNet model.

| Mean Accuracy | kFLOPs | Factor |
|---------------|--------|--------|
| Baseline      | 94.48% | 1,684.8| 0.87 |
| MobileNet     | 88.15% | 885.5  | 0.46 |
| ShuffleNet    | 88.99% | 862.4  | 0.45 |
| EffNet (ours) | 91.79% | 677.6  | 0.35 |

6. CONCLUSIONS

We have presented a novel convolutional block structure for CNNs, called EffNet, which promises to significantly reduce computational effort while preserving and even surpassing the baseline’s accuracy. Our unified blocks are made for safely replacing the vanilla convolution layers in applications for embedded and mobile hardware. As networks are reduced to a small fraction of the baseline’s FLOPs, our method present a two-fold advantage, first is the quicker architecture and second the application of a larger, deeper network becomes possible. We have also showed how such a larger network is clearly preferable to the baseline while requiring a similar number of operations.

7. REFERENCES

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