# A Simple and Effective Convolutional Filter Pruning based on Filter Dissimilarity Analysis

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Abstract: In this paper, a simple and effective filter pruning method is proposed to simplify the deep convolutional neural network (CNN) and accelerate learning. The proposed method selects the important filters and discards the unimportant ones based on filter dissimilarity analysis. The proposed method searches for filters with decent representative ability and less redundancy, discarding the others. The representative ability and redundancy contained in the filter is evaluated by its correlation with currently selected filters and left over unselected filters. Moreover, the proposed method uses an iterative procedure, so that less representative filters can be discarded evenly from the entire model. The experimental analysis confirmed that a simple filter pruning method can reduce floating point operations (FLOPs) of TernausNet by up to 89.65% on an INRIA Aerial Image Labeling dataset with an only marginal drop in the original accuracy. Furthermore, the proposed method shows promising results in comparison with other state-of-the-art methods.



## 1 INTRODUCTION

When deep CNN is adopted for computer vision tasks, the input image is convolved with many filters, extracting meaningful features from the input image. As the network grows deeper and wider, deep feature extraction plays a significant role in demonstrating excellent performance in the field of computer vision (Ahmadi et al. 2020; N. Liu et al. 2018; X. Liu et al. 2017; Liao et al. 2020; Lunga et al. 2018; Xu et al. 2018). However, the success of deep CNN comes with an over-parameterized model that hampers their applicability while deploying them on embedded devices due to difficulties, such as, large number of parameters, expensive computational cost, slow convergence and so on. Therefore, network pruning has become an essential process to compress the model and accelerate its training (C. T. Liu et al. 2019; Torfi et al. 2018; Wang et al. 2019; Wen et al. 2020). Network pruning can be performed by either weight pruning or filter pruning. Weight pruning removes unimportant connections (parameters) and results in an unstructured network (Han, Mao, and Dally 2016; Ma et al. 2021). This necessitates specialized software and hardware to recover the performance of damaged networks. Moreover, weight pruning offers only limited speedup, as most parameters of the model lie in fully connected layers and weight pruning simply reduces the number of parameters, but fails to reduce Floating Point Operations (FLOPs) significantly. For instance, the VGG16 network has 90% of its parameters in a fully connected layer, which account for 10% of computations, whereas the remaining 90% of computations is due to 10% of parameters in the convolutional layer. This has encouraged the research community to focus on exploring the filter pruning.

Filter pruning cuts out unimportant filters entirely instead of connections, resulting in structured sparsity (Shi et al. 2021; Jang, Lee, and Kim 2021; Zuo et al. 2020; Zeng et al. 2021). Here the idea is to rank the filters using a specific criteria and preserve only top ranked filters. In the past decade, numerous methods have been suggested to evaluate the filter importance, including, $l_1$ norm, $l_2$ norm, entropy measure, geometric mean, Taylor expansion and many more (Han et al. 2015; Luo and Wu 2017; He et al. 2019; Molchanov et al. 2017). These magnitude based pruning methods calculate the importance based on filter itself, but do not take filter correlation into account. Intuitively, the filters of the convolutional neural networks are not independent. Even though



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different filters try to learn different features, there exists potential similarity/correlation among them leading to performance degradation of deep CNN. Therefore, we believe that filters could be removed by taking correlation among them into account. Despite the success of the existing filter pruning approaches, we have identified a major shortcoming: filter importance is measured independently while totally ignoring the redundancy among filters. Any convolutional layer generally consists of many similar/redundant filters. From an information theory point of view, these correlated filters do not provide additional discriminant information. Instead, they increase the computational burden. Therefore, in this paper, we propose a simple and efficient approach to obtain compact deep CNNs by selecting important filters and eliminating the unimportant ones based on filter correlation analysis. The proposed method adopts a sequential search process to obtain the final subset of important filters. The major contributions of this work are as follows:

1. A simple and efficient approach to simplify deep CNN architectures, which is based on filter dissimilarity analysis.
2. The importance of a filter is decided by measuring its distance with other selected and unselected filters.
3. The selected filters show better representative ability and less redundancy.
4. Experimental analysis on the TernausNet and U-Net model trained with the INRIA dataset demonstrate the effectiveness of the proposed approach.

The remaining sections of the paper are organized as follows: The proposed OSFP approach is introduced in Section 2. Section 3 discusses the experiments and presents the results. Finally, we conclude this paper in Section 4.

## 2 PROPOSED FILTER PRUNING APPROACH

The proposed method compresses the CNN model by selecting the important filters while discarding the remaining ones. The method starts with an empty set and adds a filter sequentially to it. A filter is added to the final set by determining its filter priority index (FPI) which indicates the contribution of the selected filter. The FPI of the filter is computed by measuring its representative ability and redundancy with other selected and unselected filters. The filter is said to be representative if it is highly correlated (similar) with other unselected filters of the CNN model, whereas the filter is said to be less redundant if it is only marginally correlated (dissimilar) with other selected filters.

Let us consider a CNN model with $L$ convolutional layers and each $i^{\text{th}}$ layer is denoted as $L_i$. Each $L_i$ consists of $N$ filters indicated as $F_{L_i} = \{f_1, f_2, f_3, \dots, f_N\}$. The dissimilarity matrix $D$ of the filters of $F_{L_i}$ can be expressed as:

$$D = \begin{bmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,N} \\ d_{2,1} & d_{2,2} & & d_{2,N} \\ \vdots & & \ddots & \vdots \\ d_{N,1} & d_{N,2} & \cdots & d_{N,N} \end{bmatrix} \quad (1)$$

Here, $d_{i,j}$ is the dissimilarity between $i^{\text{th}}$ and $j^{\text{th}}$ filter. The value of $d_{i,j}$ depends on the type of metric used for calculating the dissimilarity between two filters. For instance, in case of the Manhattan distance ($l_1$ norm), the smaller the value of $d_{i,j}$, the higher the correlation is (two filters are similar to each other). Correspondingly, in case of the Pearson correlation coefficient (PCC), the larger the value of $d_{i,j}$, the higher the correlation is. Due to simplicity and ease of implementation, we will use Manhattan distance to compute the correlation between two filters. Moreover, it is less expensive in terms of computational costs than PCC as well as Euclidean distance ($l_2$ norm).

The proposed method assigns FPI to each filter and selects the set of important filters, discarding the unimportant ones. The process selects one filter each time resulting in a sequential search. It starts with an empty subset $\varphi$. To add the filter into the set, we need to evaluate its representative ability by measuring the relative correlation with remaining unselected filters and by measuring its redundancy. Let us assume, $\varphi_S$ and $\varphi_U$ be the set of selected and unselected filters. Consider that we need to select $m$ filters out of $N$ filters in total and have found $n$ filters ($n \in [0, m]$). To find the $(n+1)^{th}$ filter, the relative correlation of $f_i$ can be evaluated as,

$$I_U^i = \frac{1}{N-n-1} \sum_{j \in \varphi_U} d_{i,j} \quad (2)$$

Where, $I_U^i$ indicates the relative correlation of $f_i$ with respect to the remaining unselected filters. The smaller the value of $I_U^i$, the more representative the filter is. The redundancy of $f_i$ can be calculated as,

$$I_s^i = \frac{1}{n} \sum_{j \in \varphi_s} d_{i,j} \quad (3)$$

Where, $I_S^i$ indicates the redundancy of $f_i$ with respect to currently selected filters. Clearly, the larger the value of $I_S^i$, the lesser the redundancy is. Then, the priority index $I^i$ of the filter $f_i$ can be computed as,

$$I^i = \frac{I_U^i}{I_S^i} \quad (4)$$

Once the priority index of all filters has been computed, the filter with maximum index will be selected and added to the set of important filters. This process is repeated until the desired set of filters is obtained. Algorithm 1 gives the overall procedure of the proposed method for representative filter selection and pruning of remaining (weak) filters.

Algorithm 1: The proposed method for representative filter selection and pruning of weak filters.

Input: Original model *M*, Set of filters of $F_{L_i}$ from each layer $L_i$, *m* number of filters to be retained
1. For *i=1:L*
2. Compute the dissimilarity matrix *D*. Set $\varphi_S = 1$, $\varphi_U = N$, *n=1*.
3. while $n < m + 1$ do
4. Compute priority index of each filter using equation (4).
5. Add the filter with the lowest value in $\varphi_S$.
6. $n \leftarrow n + 1$
7. end while
8. End For
9. Output: Compressed model M'

# 3 EXPERIMENTS

To assess the effectiveness of the proposed approach, several tests were conducted on the INRIA Aerial Image Labeling dataset (Maggiori et al. 2017). The INRIA dataset consists of training images and test images. We have used two widely known deep CNN models for segmentation purposes, namely, TernausNet (Iglovikov and Shvets 2018) and a standard U-Net. All the experiments were performed on Intel Xeon CPU E5-2680 with four cores and NVIDIA P100 GPU. Both TernausNet and standard U-Net were trained using the deep learning framework Pytorch. The hyper-parameter setting used in the experiments is shown in Table 1. To get the baseline accuracies for each network, we train each model from scratch on INRIA dataset and follow the same data processing as TernausNet (Iglovikov and Shvets 2018). After the pruning stage, to recover the performance of the pruned model, fine-tuning is performed by training the pruned model for 15 epochs. We have used three metrics to evaluate the performance of the segmentation task, such as, validation accuracy (Val. Acc.), validation loss and Jaccard index (also known as Intersection over Union (IoU)). In order to assess the performance of the compressed model, the number of parameters and FLOPs are reported. We evaluated the proposed method on the INRIA dataset with TernausNet and U-Net by varying pruning rates and results are discussed in following subsections.

Table 1: Hyper-parameter setting re-training/ fine-tuning of pruned network.

| Hyper-parameter | Value |
|---|---|
| Number of epochs | 15 |
| Optimizer | Adam |
| Optimizer learning rate | 0.0001 |
| Optimizer betas | (0.9, 0.999) |
| Loss function | Binary cross entropy |
| Batch size | 64 |

## 3.1 TernausNet on INRIA

The experimental results for the TernausNet are reported in Table 2 and Table 3. Table 2 shows the overall performance of the proposed approach under different pruning ratios. As shown in Table 2, the baseline model achieved lowest Val. loss (0.1031), but had an enormous amount of memory (22.9 Million parameters) and a slow inference speed (23.5 Billion FLOPs). Note that the proposed approach demonstrated a significantly better performance than the unpruned model, even at higher pruning rates. Especially, at 70% pruning rate, the proposed method reduced the FLOPs by 69.75% with only 0.64% drop in the Val. Acc., which is quite negligible. As the pruning amount exceeded 70%, the performance started to degrade. TernausNet has many redundant filters. So, even when more filters were pruned, the performance degradation was still negligible in general. We can conclude that when a large amount of FLOPs and parameters are reduced, the proposed approach still achieves comparable performance. This means the proposed method effectively retains the filters, which exhibit great generalization ability.

To validate the effectiveness of the proposed approach, the performance of the proposed approach is compared with two other state-of-the-art methods, such as, magnitude based filter pruning- $l_1$ similarity (Li et al. 2017) and random pruning (Mittal et al. 2019). $l_1$ similarity based method removes the filters with smaller weight, whereas a random pruning method prunes the filters randomly. Furthermore, we have tested other dissimilarity metrics namely, PCC

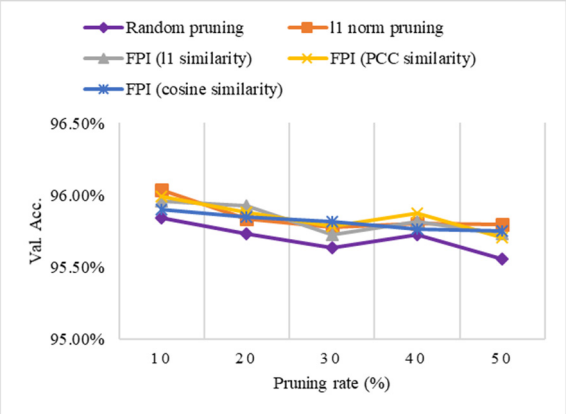
and cosine dissimilarity. The performance in terms of Val. Acc. and Val. loss after fine-tuning is recorded in Fig. 1. All approaches have shown lower performance before fine-tuning. Therefore, accuracy is restored by fine-tuning the pruned model for several epochs. Though, random pruning shows almost equal performance, it is not a robust method in practice and may lead to unstable accuracies when applied to a larger model. Compared to state-of-the-art methods, the proposed approach performs at a moderate level and shows acceptable error. Moreover, when PCC is used as a dissimilarity measure, it reduces the redundancy better and performs comparably better than state-of-the-art methods as well as other metrics. This analysis completely confirms effectiveness of different metrics in dissimilarity measures of convolutional filters and flexibility for filter pruning.

Table 2: Overall Performance of our approach on TernausNet with different pruning rate.

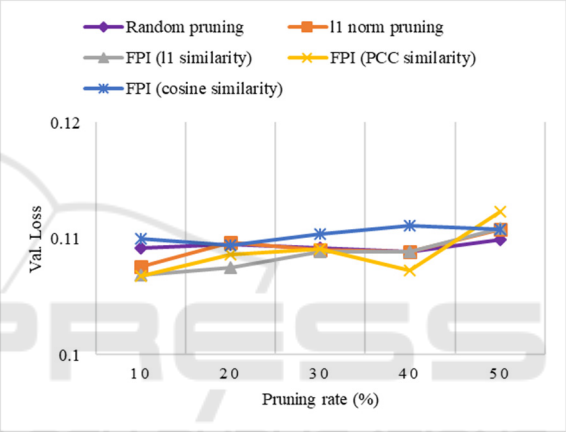
| Pruning rate (%) | Number of Param. (Million) | FLOPs (Billion) | Val. Acc. (%) | Val. loss | IoU |
|---|---|---|---|---|---|
| Baseline (unpruned) | 22.9 | 23.5 | 96.02 | 0.1031 | 0.4599 |
| 10 | 21.0 | 21.2 | 95.95 | 0.1069 | 0.4653 |
| 20 | 19.0 | 18.9 | 95.92 | 0.1075 | 0.4602 |
| 30 | 17.0 | 16.6 | 95.72 | 0.1109 | 0.4566 |
| 40 | 15.0 | 14.2 | 95.81 | 0.1089 | 0.4567 |
| 50 | 13.0 | 11.8 | 95.73 | 0.1109 | 0.4539 |
| 60 | 11.1 | 9.48 | 95.46 | 0.1173 | 0.4397 |
| 70 | 9.09 | 7.12 | 95.38 | 0.1193 | 0.4338 |
| 80 | 7.12 | 4.79 | 94.90 | 0.1314 | 0.4122 |
| 90 | 5.15 | 2.43 | 94.20 | 0.1465 | 0.3759 |

Table 3: Pruning statistics for TernausNet on Inria dataset under different pruning rates.

| Pruning rate (%) | Reduction in number of Param. | Reduction in FLOPs | Change in Val. Acc. |
|---|---|---|---|
| Baseline | 0% | 0% | -- |
| 10 | 8.57% | 9.73% | -0.06% |
| 20 | 17.19% | 19.75% | -0.10% |
| 30 | 25.77% | 29.65% | -0.30% |
| 40 | 34.39% | 39.66% | -0.21% |
| 50 | 43.15% | 50.00% | -0.29% |
| 60 | 51.73% | 59.73% | -0.57% |
| 70 | 60.34% | 69.75% | -0.64% |
| 80 | 68.93% | 79.65% | -1.13% |
| 90 | 77.54% | 89.66% | -1.82% |




(a)




(b)

Figure 1: Performance of different filter pruning approaches on TernausNet under different pruning rate. The model was trained, fine-tuned and validated on a cropped image of 256 × 256 resolution. (a) Val. Acc. vs pruning rate (b) Val. loss vs. pruning rate.

## 3.2 U-Net on INRIA

Table 4 and 5 show the experimental results for a U-Net. As shown in Table 4, the baseline model achieved lowest Val. loss (0.1054), but had an enormous amount of memory (31 Million parameters) and a slow inference speed (46 Billion FLOPs). At 70% pruning rate, the Val. Acc. of the proposed method was reduced by 0.95% in comparison with the baseline model, but the number of parameters was reduced by 63.62% and the necessary FLOPs were also significantly reduced by 69.60%. In other words, the proposed method offers excellent performance in terms of Val. Acc., FLOPs and number of parameters over different pruning rates. This excellent performance is in line with the results of the TernausNet. We can conclude that when

a large amount of FLOPs and parameters are reduced, the proposed approach still obtains comparable performance. This means the proposed method effectively retains the filters which exhibit great generalization ability. Moreover, both the models are trained from scratch instead of using pre-trained weights and results show that the proposed approach is independent of the pre-trained model's performance and helps filters to learn their responsibility.

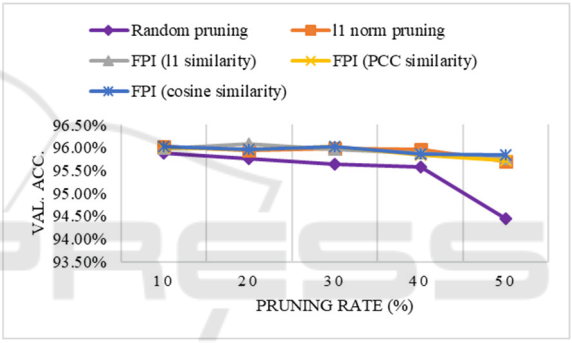
To validate the effectiveness of the proposed approach, the performance of the proposed approach is compared with two other state-of-the-art methods, such as, magnitude based filter pruning- $l_1$ similarity and random pruning. Furthermore, we have tested other dissimilarity metrics namely, PCC and cosine dissimilarity. The performance in terms of Val. Acc. and Val. loss after fine-tuning is recorded in Fig. 2. All approaches have shown lower performance before fine-tuning. Therefore, accuracy is restored by fine-tuning the pruned model for several epochs. Random pruning method has achieved lowest Val. Acc. at all pruning rates among all methods. Compared to state-of-the-art methods, the proposed approach performs at a moderate level and shows acceptable error. Moreover, when PCC is used as a dissimilarity measure, it reduces the redundancy better and performs comparably better than state-of-the-art methods as well as other metrics. This analysis completely confirms effectiveness of different metrics in dissimilarity measures of convolutional filters and flexibility for filter pruning.

Table 4: Overall Performance of our approach on U-Net with different pruning rate.

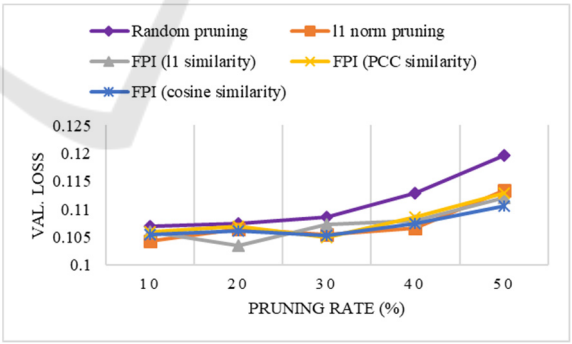
| Pruning rate (%) | Number of Param. (Million) | FLOPs (Billion) | Val. Acc. (%) | Val. loss | IoU |
|---|---|---|---|---|---|
| Baseline | 31.0 | 46.0 | 96.13 | 0.1054 | 0.4714 |
| 10 | 28.2 | 41.6 | 96.04 | 0.1043 | 0.4647 |
| 20 | 25.4 | 37.0 | 95.98 | 0.1056 | 0.4633 |
| 30 | 22.6 | 32.3 | 95.98 | 0.1065 | 0.4648 |
| 40 | 19.8 | 27.8 | 95.87 | 0.1088 | 0.4541 |
| 50 | 16.9 | 23.0 | 95.64 | 0.1142 | 0.4486 |
| 60 | 14.1 | 18.6 | 95.39 | 0.1212 | 0.4361 |
| 70 | 11.3 | 14.0 | 95.27 | 0.1217 | 0.4292 |
| 80 | 8.47 | 9.32 | 94.82 | 0.1337 | 0.4144 |
| 90 | 5.65 | 4.75 | 92.97 | 0.1721 | 0.3203 |

Table 5: Pruning statistics for U-Net on Inria dataset under different pruning rates.

| Pruning rate (%) | Reduction in number of Param. | Reduction in FLOPs | Change in Val. Acc. |
|---|---|---|---|
| Baseline | 0% | 0% | -- |
| 10 | 9.03% | 9.66% | -0.09% |
| 20 | 18.03% | 19.58% | -0.15% |
| 30 | 27.10% | 29.86% | -0.15% |
| 40 | 36.13% | 39.63% | -0.26% |
| 50 | 45.48% | 50.05% | -0.49% |
| 60 | 54.52% | 59.61% | -0.74% |
| 70 | 63.55% | 69.60% | -0.86% |
| 80 | 72.68% | 79.76% | -1.31% |
| 90 | 81.77% | 89.68% | -3.16% |




(a)




(b)

Figure 2: Performance of different filter pruning approaches on U-Net under different pruning rate. The model was trained, fine-tuned and validated on a cropped image of $256 \times 256$ resolution. (a) Val. Acc. vs pruning rate (b) Val. loss vs. pruning rate.

# 4 CONCLUSION AND FUTURE WORK

In this paper, a simple and effective filter pruning method based on filter correlation analysis is proposed. The new method searches for a subset of filters that can reliably and adequately represent the structure of the original model. The proposed method iteratively adds filters with better representative ability and less redundancy into the final set of retained filters, discarding the others. Unlike the existing norm based criterion, the proposed method explicitly considers the correlation among filters. The pruned model with the proposed method learns effectively with few filters. Thus, when pruning a TernausNet trained on the INRIA dataset by the proposed method, FLOPs reduction rates are as high as 89.65% accompanied by a negligible drop in the Val. Acc. ($< 2\%$). The experimental analysis on TernausNet and U-Net confirms the robustness of the proposed approach. However, iterative searching for the representative filters takes some good amount of time. Therefore, it will be our future work to explore a way to render the method faster.

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