

Deep Model Compression based on the Training History[☆]

S.H. Shabbeer Basha^{a,*}, Mohammad Farazuddin^b, Viswanath Pulabaigari^b, Shiv Ram Dubey^c, Snehasis Mukherjee^d

^a School of Computer Science and Engineering, RV University, Bangalore, Karnataka 560059, India.

^b Indian Institute of Information Technology Sri City, Chittoor, Andhra Pradesh 517646, India.

^c Indian Institute of Information Technology Allahabad, Prayagraj, Uttar Pradesh 211015, India.

^d Shiv Nadar University, Greater Noida, Uttar Pradesh 201314, India.

ARTICLE INFO

Communicated by D. Wu

Keywords:

Convolutional Neural Networks
Filter pruning
Finetuning
Optimization

ABSTRACT

Deep Convolutional Neural Networks (DCNNs) have shown promising performances in several visual recognition problems which motivated the researchers to propose popular architectures such as LeNet, AlexNet, VGGNet, ResNet, and many more. These architectures come at a cost of high computational complexity and parameter storage. To get rid of storage and computational complexity, deep model compression methods have been evolved. We propose a “History Based Filter Pruning (HBFP)” method that utilizes network training history for filter pruning. Specifically, we prune the redundant filters by observing similar patterns in the filter’s ℓ_1 -norms (absolute sum of weights) over the training epochs. We iteratively prune the redundant filters of a CNN in three steps. First, we train the model and select the filter pairs with redundant filters in each pair. Next, we optimize the network to ensure an increased measure of similarity between the filters in a pair. This optimization of the network facilitates us to prune one filter from each pair based on its importance without much information loss. Finally, we retrain the network to regain the performance, which is dropped due to filter pruning. We test our approach on popular architectures such as LeNet-5 on MNIST dataset; VGG-16, ResNet-56, and ResNet-110 on CIFAR-10 dataset, and ResNet-50 on ImageNet. The proposed pruning method outperforms the state-of-the-art in terms of FLOPs reduction (floating-point operations) by **97.98 %**, **83.42 %**, **78.43 %**, **74.95 %**, and **75.45 %** for LeNet-5, VGG-16, ResNet-56, ResNet-110, and ResNet-50, respectively, while maintaining the less error rate. The source code is available at: <https://github.com/shabbeersh/HBFP>.

1. Introduction

In recent years, Convolutional Neural Networks (CNN) have gained significant attention from researchers, especially for visual recognition tasks, due to their impeccable performance in several tasks including object recognition and detection [1], speech recognition [2]. The wide usage of deep CNNs in numerous applications (especially in vision) creates an increasing demand for memory (parameter storage) and computation. To address this key issue, various attempts have been made in the literature. One such attempt focuses on training the deep CNNs with limited data [3–5]. Another line of research has shown better performance by reducing the overhead of computational power and memory storage, which mainly focuses on model compression by two approaches: pruning connections [6,7] and pruning filters [8–10].

Typically, increasing the size (requires more storage space) of a deep neural network makes deploying the model difficult on low-end (resource constraint) devices such as mobile devices and embedded

systems. For example, VGG-16 [11] has 138.34 million parameters which require storage space of more than 500 MB. To reduce the resource overhead of deep CNNs, many attempts have been made to prune less-important connections and filters from a CNN which results in architectures with compressed design. Most of the works on deep model compression can be broadly categorized into four classes [12]. The first class [6,13] of methods are focused on introducing sparsity into the model parameters. The second class [14–16] of methods are aimed at quantization-based pruning. The third class of methods are dedicated to compressing the networks using filter decomposition [17, 18]. The fourth class of methods are focused on pruning unimportant filters [8,19,20]. The proposed training History Based Filter Pruning (HBFP) method belongs to the fourth category.

In general, filter pruning methods require some metric to calculate the importance of a filter. Several metrics have been proposed to calculate the importance of a filter. For instance, Abbasi et al. [19]

[☆] This research was partly conducted during the corresponding author’s affiliation with Indian Institute of Information Technology Sri City (IIIT Sri City).

* Corresponding author.

E-mail addresses: shabbeerb@rvu.edu.in (S.H.S. Basha), farazuddin.m17@iiits.in (M. Farazuddin), viswanath.p@iiits.in (V. Pulabaigari), srdubey@iiita.ac.in (S.R. Dubey), snehasis.mukherjee@snu.edu.in (S. Mukherjee).

<https://doi.org/10.1016/j.neucom.2024.127257>

Received 20 April 2022; Received in revised form 21 February 2023; Accepted 9 January 2024

Available online 17 January 2024

0925-2312/© 2024 Elsevier B.V. All rights reserved.

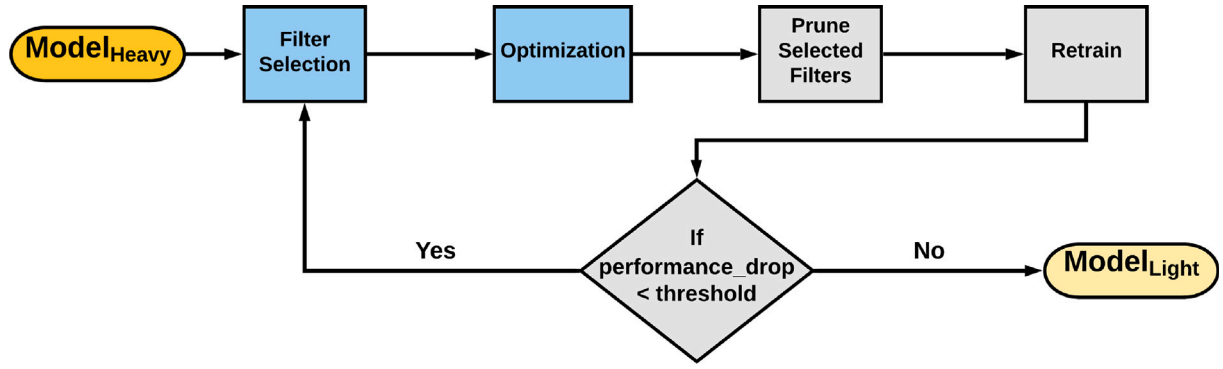


Fig. 1. Initially, we start with a heavier model, after identifying the redundant filters, instead of pruning the filters naively at this stage, we optimize the model to minimize the complimentary information loss that will occur due to filter pruning. After optimizing the network with the custom regularizer, one filter from each redundant filter pair is pruned. Later the network is re-trained to regain the classification performance. This process is repeated iteratively to obtain a lightweight CNN.

employed a brute-force technique to prune the filters sequentially that contribute less to the classification performance. However, the brute-force technique is inefficient while dealing with large neural networks, such as AlexNet [21] and VGG-16 [11]. Li et al. [10] pruned the unimportant filters based on their ℓ_1 -norm. They assumed that the filters with a high ℓ_1 -norm are most probably important and will have a larger influence on the relevance of the generated feature map.

In this paper, we introduce a novel method for pruning redundant filters based on the training history. We iteratively prune redundant filters from a CNN in three stages. First, we select some ($M\%$) of filter pairs as redundant for which the sum of the absolute value of the difference between the filter's ℓ_1 -norm over training epochs is minimum. Next, instead of pruning the filters directly, we reduce the difference between the filter's ℓ_1 -norm in respective epochs (which we call optimization) to minimize the complimentary information loss and then prune one filter from each pair based on its magnitude. Finally, we fine-tune (re-train) the network to gain the classification performance, which is decreased due to filter pruning. We consider the difference between ℓ_1 -norms (magnitude) of the filters as a metric to verify how similar they are throughout the model training. If the magnitude of one of the filters in a pair improves due to subsequent weights update, then such filters will not be selected for pruning. The intuition behind using this metric is to find the filters that are exhibiting stable behavior. However, the proposed method can be adapted to any other magnitude-based methods and similarity-based pruning methods (cosine similarity), etc.

We consider ℓ_1 -norm of filters across the training epochs to select and prune the redundant filters due to its simplicity. However, our method can be adapted to any other metric like ℓ_2 -norm, Cosine Similarity, and so on. The high-level view of the proposed method is outlined in Fig. 1.

The remaining paper is organized as follows: the related works are compiled in Section 2; Preliminaries and notations are presented in Section 3; The proposed History Based Filter Pruning (HBFP) method is explained in Section 4; The experimental pruning results are examined in Section 5 along with the analysis and discussion; Finally, the concluding remarks are made in Section 6 along with the future directives.

2. Related works

We illustrate the efforts found in the published literature for deep model compression by classifying the approaches into the following major categories.

2.1. Connection pruning

Connection pruning methods induce sparsity into the neural network. A simple approach is to prune the connections with unimportant

weights (parameters) [22]. However, this method requires quantifying the significance of the parameters. In this direction, Lecun et al. [23] and Hassib et al. [24] have utilized second-order derivative information to quantify the importance of network connections (parameters). However, computing second-order derivatives of all the connections is expensive. Chen et al. [13] used a low-cost hash function to group the weights into a single bucket such that weights in the same bucket have roughly the same parameter value. Hu et al. [25] introduced a network trimming approach that iteratively prunes the zero-activation neurons. Wu et al. [7] proposed a method called BlockDrop to dynamically learn which layers to execute during the inference to reduce the total computation time. Han et al. [6] developed a pruning technique based on the absolute value of the parameter. In [6], the parameters with the absolute value below a certain threshold are fixed to zero. These pruning methods are suggested in scenarios where the majority of the network parameters belong to Fully Connected (FC) layers. For deep models such as ResNet [26] and DenseNet [27], these types of pruning methods might not be suitable. However, the use of modern deep learning models for different applications is a recent trend. Ding et al. [28] developed a network pruning method in which authors aim to make the filters identical before pruning them to minimize the information loss.

2.2. Weight quantization

The weight (parameter) quantization method found in the literature is extensively used for deep model compression [6]. Han et al. [6] compressed the deep CNNs by integrating connection pruning, quantization, and Huffman coding. Similarly, Tung et al. [29] combined pruning and weight quantization for deep model compression. Floating-point quantization is performed in [30] for creating efficient deep neural networks. Binarization [15] is another popular quantization technique used for model compression in which each floating-point value is mapped to a binary value. Bayesian approximation methods [14] are used for deep model quantization. The weight quantization-based methods aim to speed up the execution process by reducing the complexity of number representation and arithmetic & logical operations. However, these methods require the support of special hardware to capture the benefit of network compression. Recently, two-way model compression schemes are proposed in [31,32] in which both filter decomposition and pruning are performed.

2.3. Filter decomposition

As reported in [33], deep neural networks are over-parameterized that indicates that the parameters of a layer can be recovered from a subset of the actual parameters that belong to the same layer. Motivated by this work, many low-rank filter decomposition works have been

evolved [17,18]. Unlike filter pruning, which aims at pruning the unimportant filters, these methods decrease the computational cost of the network. In this direction, Denton et al. [8] utilized the linear structure of CNNs to find a suitable low-rank approximation for the parameters by allowing minimal loss to the network performance. Zhang et al. [20] made use of subsequent non-linear units for learning low-rank filter decomposition to speed up the learning process. Lin et al. [34] introduced a low-rank decomposition method to decrease the redundant features corresponding to convolutional kernels and dense layer matrices. Recently, EDropout is proposed in [35] which uses a binary state pruning vector to prune the filters/units from convolutional, dense layers.

2.4. Filter pruning

Compared to other network pruning methods, filter pruning methods are generic, and do not require the support of any special software/hardware. Due to this reason, filter pruning methods have gained popularity among researchers in recent years. In general, filter pruning methods [9,36–39] compute the importance of filters so that unimportant filters can be pruned from the model. In filter-pruning methods, after each iteration, retraining is required to regain the classification performance, which is dropped due to pruning the filters. Abbasi et al. [19] proposed a greedy-based compression scheme for filter pruning. Similarly, Li et al. [10] employed a greedy approach to prune the filters with less filter norm. In [40], redundant channels are investigated based on the distribution of channel parameters. Ayinde et al. [41] utilized relative cosine distance among the filters for filter pruning. Ding et al. [42] proposed an auto-balanced method to transfer the representation capacity of a convolutional layer to a fraction of filters belong to the same layer. Other methods such as Taylor expansion [43], low-rank approximation [8,20,44], group-wise sparsity [45–48], and many more are employed to prune the filters from deep neural networks. Zhang et al. [49] introduced a unified framework that can be used to induce sparsity at various granularities like filter-wise, channel-wise, and shape-wise sparsity. Recently, Lin et al. [36] proposed a filter pruning method based on the rank of feature maps in each layer such that the filters contributing to low-rank feature maps can be pruned. Chen et al. [50] developed a filter pruning method that dynamically prunes channels/filters during network training rather than iteratively pruning and re-training. Song et al. [51] introduced SP-GAN, a self-growing and pruning Generative Adversarial Network for image generation, in which, the Euclidean distance between each pair of filters is used as the metric for filter pruning. Later, a filter is randomly selected for pruning from the filter pairs having the least Euclidean distance. He et al. [52] proposed a soft-filter pruning method that allows filters to be updated during model training which results in better performance. Recently, Wang et al. [53] proposed a filter pruning method that computes the importance of filters based on the entropy of feature maps. Later, low-ranked filters are pruned from the model.

2.5. Others approaches

There have been other attempts in the literature to reduce the model complexity without compromising on the performance. Apart from the neural network compression methods discussed above, there are methods in which a small model (student) mimics the behavior of a large model (teacher). This paradigm is popularly known as Knowledge Distillation in the literature [54]. Cheng et al. [13] presented a comprehensive survey on deep model compression. In recent years, Neural Architecture Search (NAS) has gained the attention of researchers [55]. NAS methods aim at finding a suitable network architecture for a given problem with minimal human intervention. Recently, NAS methods have been used to find the optimal number of channels in layer [56]. Similarly, there are a few methods that performed filter pruning using

meta-learning [57]. There are a few methods in the literature where unimportant filters and layers are identified and pruned only once not in an iterative manner [58].

Most of the filter pruning methods discussed so far, prune the unimportant filters. However, these methods may not remove the filters that are consistently redundant throughout the network training. We propose a novel filter pruning technique that utilizes the training history to find the filters to be pruned. Moreover, in contrast to other classes of pruning methods, the proposed filter pruning method does not require the support of any additional software/hardware. In brief, the contributions of this research can be summarized as follows,

- We propose a novel method for pruning filters from convolutional layers based on the training history of a deep neural network. The proposed method facilitates the identification of stable and redundant filters throughout the training that can have a negligible effect on performance after pruning.
- We introduce an optimization step (custom regularizer) to reduce the information loss incurred due to filter pruning. It is achieved by increasing the redundancy level of selected filters for pruning.
- To establish the significance of the proposed pruning method, experiments are conducted on benchmark CNNs like LeNet-5 [59], VGG-16 [11], ResNet-50, ResNet-56, and ResNet-110 [26]. The validation of the proposed pruning method is performed over three benchmark classification datasets, including MNIST, CIFAR-10, and ImageNet.

3. Preliminaries and notations

In this section, we discuss the background details like computing the Floating Point Operations (FLOPs) involved in a CNN and the notations used in this paper.

3.1. Calculating floating point operations

To compare the performance of various CNN models, we primarily use the accuracy on the validation set as a metric to compare which model is the most accurate. However, when there are constraints on computational resources, we use the number of Floating Point Operations (FLOPs) as a metric to compare which model is more efficient. We use the terms “Heavy” and “Light” to represent the models with a higher and lower number of FLOPs, respectively. For a given input feature map, the number of FLOPs involved in a convolutional layer L_i , i.e., $(FLOP_{conv}(L_i))$, is computed as follows,

$$FLOP_{conv}(L_i) = F * F * C_{in} * H_{out} * W_{out} * C_{out}. \quad (1)$$

Here, $F * F$ is the spatial dimension of the filter, C_{in} is the number of input channels of the input feature map, H_{out} and W_{out} are the height and width of the output feature map, and C_{out} is the number of channels in the output feature map. Similarly, for a given input feature map, the number of FLOPs for a Fully Connected (FC) or dense layer D_j , i.e., $(FLOP_{fc}(D_j))$, is given as,

$$FLOP_{fc}(D_j) = C_{in} * C_{out}. \quad (2)$$

For a model with K convolutional layers and N fully-connected layers, the total number of FLOPs is calculated as,

$$FLOP_{total} = \sum_{i=1}^K FLOP_{conv}(L_i) + \sum_{j=1}^N FLOP_{fc}(D_j). \quad (3)$$

3.2. Notations

Consider a convolutional layer L_i of a CNN, which has n filters, i.e., $\{f^1, f^2, f^3, \dots, f^n\}$. Any two filters f^i, f^j belong to the k th layer of a CNN are denoted as f_k^i, f_k^j , respectively. For instance, if the

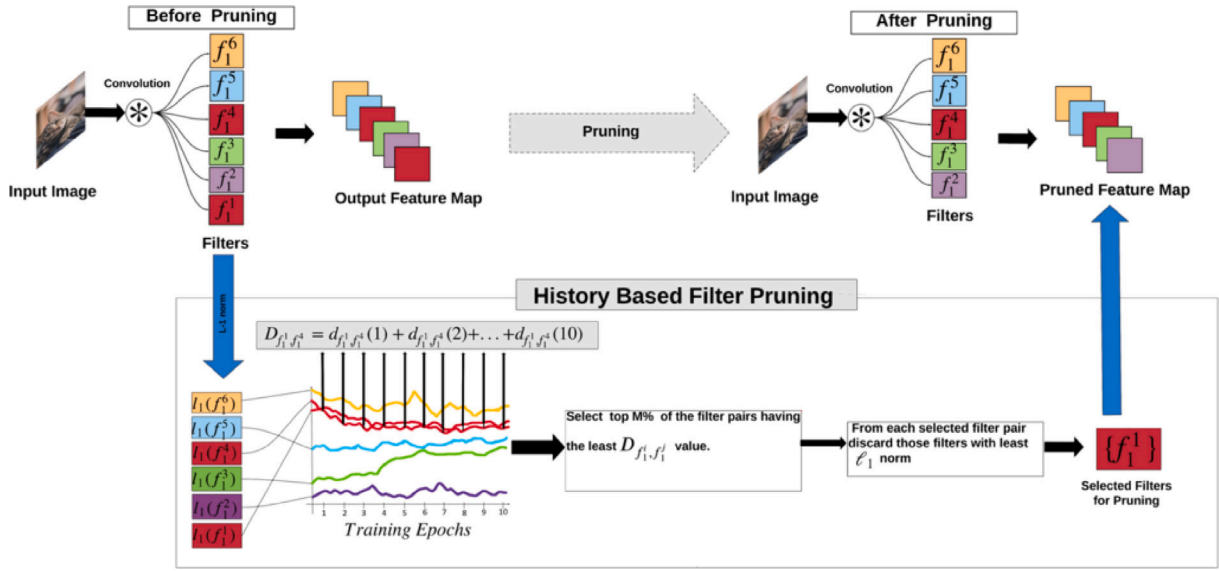


Fig. 2. The overview of the proposed pruning method. At each iteration, we compute the sum of differences $D_{f_k^i, f_k^j}$ of all filter pairs. In filter selection stage, we choose $M\%$ of filter pairs for which $D_{f_k^i, f_k^j}$ is minimum. Here, filters f_k^1 and f_k^2 have the least $D_{f_k^i, f_k^j}$ (absolute point-to-point difference), so we select them as a pair and discard one from the pair with least magnitude. The feature maps corresponding to the pruned filters get dropped.

filter f_k^i is of dimension $3 \times 3 \times 3$ then it consists of 27 parameters, i.e., $\{w_{k,1}^i, w_{k,2}^i, w_{k,3}^i, \dots, w_{k,27}^i\}$. Here ‘ k ’ represents the index of convolutional layer and ‘ i ’ denotes the filter index.

Initially, our method computes the ℓ_1 -norm of each filter within the same convolutional layer using the formula given in Eq. (4). For example the ℓ_1 -norm of filter f_k^i is computed as follows,

$$\ell_1(f_k^i) = \|f_k^i\|_1 = \sum_{p=1}^{27} |w_{k,p}^i|, \quad (4)$$

where p is the number of parameters in the filter f_k^i .

Next, we compute the absolute difference between the ℓ_1 -norms of each filter pair at every epoch as shown in Eq. (5). The absolute difference between $\ell_1(f_k^i)$ and $\ell_1(f_k^j)$ is computed as follows,

$$d_{f_k^i, f_k^j}(t) = |\ell_1(f_k^i) - \ell_1(f_k^j)|. \quad (5)$$

Here, ‘ t ’ indicates the epoch number. Then, this difference is summed over all the epochs and denoted by $D_{f_k^i, f_k^j}$. The sum of differences of filter pairs over the training epochs is considered as the metric for filter pruning and given as,

$$D_{f_k^i, f_k^j} = \sum_{t=1}^N d_{f_k^i, f_k^j}(t), \quad (6)$$

where ‘ N ’ indicates the maximum number of epochs used for training the networks.

Our method computes the sum of differences of pairs $D_{f_k^i, f_k^j}$ value for n_{C_2} filter pairs (assuming a convolutional layer has n filters). The total difference $D_{f_k^i, f_k^j}$ which is summed over all the epochs is used for filter selection. More concretely, the top $M\%$ of the filter pairs (from n_{C_2} pairs in the same layer) with the least $D_{f_k^i, f_k^j}$ value are formed as redundant filter pairs which represent roughly the same information. The overview of the proposed HBFP method is presented in Fig. 2. The proposed History Based Filter Pruning (HBFP) method involves two key steps, (i) Filter selection and (ii) Optimization which are presented in the next section.

4. Proposed training History Based Filter Pruning (HBFP) method

Our pruning method aims at making a deep neural network computationally efficient. This is achieved by pruning the redundant filters

whose removal does not cause much hindrance to the classification performance. We identify the redundant filters by observing similar patterns in the weights (parameters) of filters during the network training, which we refer to as the network’s training history. We start with a pre-trained CNN model. During the network training, we observe and form pairs of filters whose weights follow a similar trend over the training epochs. In each iteration, we pick some ($M\%$) of the top filter pairs with high similarity (based on the D value computed using Eq. (6), low D value means high similarity). Instead of pruning the filters at this stage, we increase the similarity between the filters that belong to the selected filter pairs by introducing an optimization step. This optimization is achieved with a custom regularizer whose objective is to minimize the difference between the filter’s norms (belong to a filter pair) at each epoch. After optimization, one filter from each pair is discarded (pruned). From a filter pair, we prune one filter based on the criteria employed in [10], i.e., the filters with a higher ℓ_1 -norm are more important. Finally, to recover the model from the performance drop which is incurred due to filter pruning, we retrain the pruned model. This process corresponds to one iteration of the proposed pruning method which is demonstrated in Fig. 1. This whole process is repeated until the model’s performance drops below a certain threshold. Our main contributions are made specifically in the filter selection and optimization steps.

4.1. Filter selection

In the beginning, our method takes a heavy-weight CNN and selects the top $M\%$ of filter pairs from each convolutional layer for which the difference D computed in Eq. (6) is minimum. More concretely, the filter pair having the least $D_{f_k^i, f_k^j}$ value is formed as the first redundant filter pair. Similarly, the next pair having the second least $D_{f_k^i, f_k^j}$ value is formed as another filter pair, and so on. Likewise, in each iteration, $M\%$ of filter pairs from each convolutional layer are selected as redundant which are further considered for optimization. Let us define two more terms that are used in the proposed pruning method. “Qualified-for-pruning (Q_i)” and “Already Pruned (P_i)”. Here Q_i represents the set of filter pairs that are ready (selected) for pruning from a convolutional layer L_i . Whereas, P_i indicates the filters that are pruned from the network (one filter from each pair of Q_i). Hence, if $M\%$ of filter pairs are chosen in Q_i , then $|P| = M\%$, i.e., from each convolutional layer $M\%$ of filters are pruned in every iteration by the proposed method.

4.2. Optimization

Singh et al. [60] reported that introducing an optimization with a custom regularizer decreases the information loss incurred due to filter pruning. Motivated by this work, we add a new regularizer to the objective function to reduce the difference $d_{f_k^i, f_k^j}(t)$ between the filters belonging to Q_i at each epoch during network training, i.e., increasing the similarity between the filters belong to the same pair. Let $C(W)$ be the objective function (Cross-entropy loss function) of the deep convolutional neural network with W as the network parameters. To minimize the information loss and to maximize the regularization capability of the network, we employ a custom regularizer to the objective function, which is given as follows:

$$C_1 = \exp \left(\sum_{f_k^i, f_k^j \in Q_i} d_{f_k^i, f_k^j}(t) \right), \quad (7)$$

where t denotes the epoch number and $t \in 1, 2, 3, \dots, N$ (assuming we train the model for N epochs). With this new regularizer, the final objective of the proposed HBFP method is given by,

$$W = \arg \min_W \left(C(W) + \lambda * C_1 \right), \quad (8)$$

where λ is the regularizer term which is a hyperparameter. Optimizing the Eq. (8) decreases the difference $d_{f_k^i, f_k^j}$ between the filter pairs that belong to the set Q_i at every epoch without affecting the model's performance much.

4.3. Pruning and re-training

Using the process of minimizing the difference $d_{f_k^i, f_k^j}$ between the filters corresponding to a pair (which belongs to Q_i), we can increase the similarity between the filters that belong to the same filter pair. Thereby, one filter is pruned from each pair without affecting the model's performance much. The pruned model contains the reduced number of trainable parameters W' ,

$$W' = W \setminus \{p_1, p_2, \dots, p_k\}, \quad (9)$$

where p_1, p_2, \dots, p_k are the filters that are selected for pruning after optimization. Further, we re-train the network w.r.t. the reduced parameters W' to regain the classification performance. As we prune the redundant filters from the network, the information loss is minimum. Therefore, re-training (fine-tuning) makes the network to recover the loss incurred due to filter pruning.

5. Experiments and results

To demonstrate the significance of the proposed history based filter pruning method, we utilize four popular deep learning models, VGG-16 [11], ResNet-50, ResNet-56, and ResNet-110 [26]. All the experiments are conducted on NVIDIA GTX 1080 Titan Xp GPU. Through our experimental results, we observe that our method obtains state-of-the-art model compression results for all the above-mentioned CNNs. Similar to [60], the regularizer term λ is set to 1 for LeNet-5 and ResNet-50/56/110. However, we empirically observe that the value of λ as 0.8 gives better results for VGG-16. We prune $M\%$ of the filters from each convolutional layer simultaneously. The $M\%$ is considered as 10% for LeNet-5, VGG-16. Whereas, from ResNet-56, ResNet-110, and ResNet-50, we prune 2, 4, 8 filters from each convolutional layer corresponding to three blocks. We repeat this pruning process until there is a performance drop below a certain threshold, which is also a hyperparameter. In our experiments, we set the threshold value 1%, 2%, 2%, and 3% for LeNet-5 [59], VGG-16 [11], ResNet-56/110 [26], ResNet-50 [26] models, respectively. Next, we discuss the datasets utilized for conducting the experiments and then we present a comprehensive results analysis and discussion.

5.1. Datasets

In this work, we use three popular and benchmark image classification datasets, namely MNIST, CIFAR-10, and ImageNet to conduct the experiments.

5.1.1. MNIST

The MNIST dataset [61] consists the images of hand-written digits ranging from 0 to 9. This dataset has 60,000 training images with 6000 training images per class and 10,000 test images with 1000 test images per class. The dimension of the image is $28 \times 28 \times 1$. The LeNet-5 [60] is trained from scratch on MNIST.

5.1.2. CIFAR-10

CIFAR-10 [62] is the most widely used tiny-scale image dataset which has images belonging to 10 object categories. The dimension of the image is $32 \times 32 \times 3$. This dataset contains a total of 60,000 images with 6000 images per class, out of which 50,000 images (i.e., 5000 images per class) are used for both training and fine-tuning the network and the remaining 10,000 images (i.e., 1000 images per class) are used for validating the network performance.

5.1.3. ImageNet

ImageNet [63] is a large-scale visual recognition image dataset consisting of 1.2 Million training images, and 50,000 validation images belonging to 1000 object categories. We have downsampled the image dimension from $256 \times 256 \times 3$ to $224 \times 224 \times 3$ to conduct the experiments.

5.2. LeNet-5 on MNIST

We utilize LeNet-5 architecture which has two convolutional layers *Conv1* and *Conv2* with 20 and 50 filters, respectively, of spatial dimension 5×5 . The first convolutional layer *Conv1* is followed by a max-pooling layer *Max_pool1* with 2×2 filter which results in a feature map of dimension $12 \times 12 \times 20$. Similarly, the second convolutional layer *Conv2* is followed by another max-pooling layer *Max_pool2* with 2×2 dimensional filter which results in a $4 \times 4 \times 50$ dimensional feature map. The feature map resulted by *Max_pool2* layer is flattened into an 800×1 dimensional feature vector which is given as input to the first Fully Connected (FC) layer *FC1*. The *FC1* and *FC2* layers have 500 and 10 neurons, respectively. The LeNet architecture corresponds to 4,31,080 trainable parameters and 4.4M FLOPs.

We conduct a pruning experiment on LeNet-5 over the MNIST dataset using the proposed HBFP method. For LeNet-5, VGG-16, we conduct two series of experiments by pruning 10%, 20% of filters from each convolution layer. We also observe a higher drop in the performance when 20% of the filters are pruned. So, we chose to prune 10% of the filters from each convolution layer for LeNet-5, VGG-16 models. Training the network from scratch results in a 0.83% base error. The comparison among the benchmark pruning methods for LeNet-5 is shown in Table 1. Compared to the previous pruning methods, the proposed HBFP method achieves a higher reduction in the FLOPs, i.e., 97.98%, however, still results in a less error rate, i.e., 1.4%. Structured Sparsity Learning (SSL) method pruned 93.42% FLOPs with 1% error rate. From Table 1 (the rows corresponding to the proposed HBFP method), we can examine that the proposed method achieves better classification performance with a high percent of pruning compared to other methods. The previous work on Correlation Filter Pruning (CFP) by Singh et al. [60] has reported a similar FLOPs reduction, i.e., 97.98%, however, their error rate is 1.77% which is quite high compared to our method. Singh et al. [60] reported that employing a regularizer (in the form of an optimization) reduces the information loss that occurs due to filter pruning. Motivated by this work, we also optimize the network to increase the similarity between the filters belonging to a redundant filter pair. In this process, we reproduce the

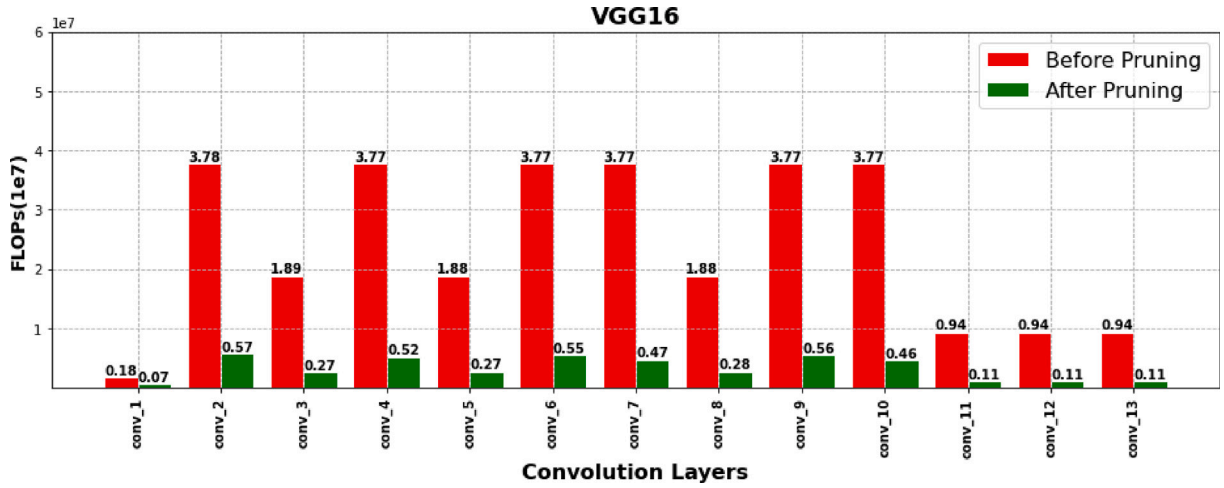


Fig. 3. The total number of FLOPs involved in each convolutional layer before and after pruning for VGG-16 trained on CIFAR-10 using the proposed history based filter pruning approach.

Table 1

The pruning results of LeNet-5 on MNIST dataset. The rows corresponding to HBFP-I, HBFP-II, HBFP-III, and HBFP-IV indicate the pruning results of the last four iterations of the proposed method.

Method	r1, r2	Top-1% error	Remaining FLOPs (Drop %)
Baseline	20,50	0.83	4.4M (0.0%)
Sparse-VD [64]	–	0.75	2.0M (54.34%)
Haider et al. [58]	–	2.52	0.44M (89.95%)
SBP [65]	–	0.86	0.41M (90.47%)
SSL-3 [46]	3,12	1.00	0.28M (93.42%)
HBFP-I (Ours)	4,5	0.98	0.19M (95.57%)
GAL [66]	2,15	1.01	0.10M (95.60%)
HBFP-II (Ours)	3,5	1.08	0.15M (96.41%)
Auto balanced [42]	3,5	2.21	0.15M (96.41%)
HBFP-III (Ours)	3,4	1.20	0.13M (96.84%)
CFP [60]	2,3	1.77	0.08M (97.98%)
CFP [60] ^a	2,3	2.61	0.08M (97.98%)
HBFP-IV (Ours)	2,3	1.40	0.08M (97.98%)

^a Indicates the reproduced results. The results are arranged in the increasing order of pruned FLOPs reduction %.

results of CFP [60] for which we obtain the top-1 error rate as 2.61% with the same percent of reduction in the FLOPs (row 10 of Table 1). However, due to this additional optimization step, the pruning cost will be higher compared to other iterative pruning methods.

5.3. VGG-16 on CIFAR-10

In 2014, Simonyan et al. [11] proposed a VGG-16 CNN model that received much attention due to improved performance over ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The same architecture and settings are used in [11] with few modifications such as batch normalization layer [74] is added after every convolutional layer. The VGG-16 consists of 1,49,82,474 trainable parameters and 313.73M FLOPs.

Training the VGG-16 network from scratch enables the model to achieve 93.96% top-1 accuracy on the CIFAR-10 object recognition dataset. The comparison among the state-of-the-art filter pruning methods for VGG-16 on CIFAR-10 available in the literature is performed in Table 2. The proposed method prunes 83.42% of FLOPs from VGG-16 which results in 91.99% of top-1 accuracy. The Geometric Median method proposed in [67] reported 93.58% top-1 accuracy with a 35.9% reduction in the FLOPs. The recent works, such as HRank [36] and Correlation Filter Pruning (CFP) [60] are able to prune 76.5% and 81.93% FLOPs with the error rate of 8.77% and 7.02%, respectively, while the proposed HBFP method is able to prune 83.42% FLOPs with

Table 2

The pruning results of VGG-16 on CIFAR-10 dataset. The reported results are taken from the respective research article, except * which is reproduced.

Model	Top-1%	Remaining FLOPs (Drop %)	Remaining parameters (Drop %)
VGG-16 [11]	93.96	313.73M (0.0%)	14.98M (0.0%)
ℓ_1 -norm [10]	93.40	206.00M (34.30%)	5.40M (64.00%)
GM [67]	93.58	201.10M (35.90%)	–
VFP [40]	93.18	190.00M (39.10%)	3.92M (73.30%)
Ayinde et al. [41]	93.67	186.67M (40.50%)	3.28M (78.10%)
SSS [68]	93.02	183.13M (41.60%)	3.93M (73.80%)
FPEI [53]	92.49	177.27M (43.45%)	3.30M (77.60%)
GAL [66]	90.73	171.89M (45.20%)	3.67M (82.20%)
Chen et al. [50]	92.90	153.69M (51.01%)	5.50M (63.28%)
Haider et al. [58]	88.11	132.42M (57.79%)	1.54M (89.66%)
HBFP-I (Ours)	93.04	90.23M (71.21%)	4.20M (71.80%)
Lin et al. [69]	93.32	81.31M (74.1%)	0.74M (95.0%)
HBFP-II (Ours)	92.54	75.05M (76.05%)	3.50M (63.28%)
HRank [36]	91.23	73.70M (76.50%)	1.78M (92.00%)
HBFP-III (Ours)	92.30	62.30M (80.09%)	2.90M (80.47%)
CFP [60]*	91.83	59.15M (81.14%)	2.80M (81.10%)
CFP [60]	92.98	56.70M (81.93%)	–
HBFP-IV (Ours)	91.99	51.90M (83.42%)	2.40M (83.77%)

an error rate of 8.01%. The detailed comparison of pruning results for VGG-16 on the CIFAR-10 dataset is demonstrated in Table 2. The FLOPs in each convolutional layer before and after employing the proposed pruning method on VGG-16 over CIFAR-10 is illustrated in Fig. 3.

5.4. ResNet-56/110 on CIFAR-10

We also use the deeper CNN models such as ResNet-56 and ResNet-110 [26] to conduct the pruning experiments over the CIFAR-10 dataset using the proposed HBFP method. ResNet-56, ResNet-110 have three blocks of convolutional layers with 16, 32, and 64 filters. Training these residual models (i.e., ResNet-56 and ResNet-110) with the same parameters as in [26] produce 93.26% and 93.5% top-1 accuracies, respectively. The HBFP method prunes 2 filters from the first block which has 16 filters, 4 filters from the second block which has 32 filters, and 8 filters from the third block which has 64 filters in each iteration of the proposed method. From Table 3, it is evident that the proposed pruning method produces state-of-the-art compression results for ResNet-56 and ResNet-110 on CIFAR-10 dataset.

ResNet-56: As depicted in Table 3, both AMC [71] and CP [9] methods have reduced 50.00% FLOPs while resulting in 8.1% and 8.2% error, respectively. The HRank [36] prunes 74.1% FLOPs with 9.28% error. From Table 3, it is clear that the proposed HBFP obtains

Table 3

The pruning results of ResNet-56/110 on CIFAR-10 dataset.

Model	Top-1%	Pruned FLOPs	Remaining parameters (Drop %)
ResNet-56 [26]	93.26	125.49M (0.0%)	0.85M (0.0%)
VFP [40]	92.26	96.60M (20.30%)	0.67M (20.49%)
ℓ_1 -norm [10]	93.06	90.90M (27.60%)	0.73M (14.10%)
Ayinde et al. [41]	93.12	90.70M (27.90%)	0.65M (23.70%)
NISP [70]	93.01	81.00M (35.50%)	0.49M (42.40%)
HBFP-I (Ours)	92.42	70.81M (43.68%)	0.48M (46.38%)
AMC [71]	91.90	62.74M (50.00%)	–
CP [9]	91.80	62.74M (50.00%)	–
Chen et al. [50]	93.10	62.70M (50.03%)	0.43M (49.04%)
He et al. [52]	93.12	59.40M (50.03%)	–
Lin et al. [69]	93.27	54.0M (57.3%)	0.38M (55.5%)
RUPF [72]	93.17	53.70M (57.70%)	–
GAL [66]	90.36	49.99M (60.20%)	0.29M (65.90%)
HBFP-II (Ours)	92.25	49.22M (60.85%)	0.33M (60.85%)
Haider et al. [58]	92.13	42.03M (66.50%)	0.25M (69.52%)
HRank [36]	90.72	32.52M (74.10%)	0.27M (68.10%)
HBFP-III (Ours)	91.79	31.54M (74.91%)	0.21M (74.90%)
CFP [60]*	91.37	31.54M (74.91%)	0.21M (74.90%)
CFP [60]	92.63	29.50M (76.59%)	3.40M (77.14%)
Ding et al. [73]	92.66	27.82M (77.83%)	–
HBFP-IV (Ours)	91.42	27.10M (78.43%)	0.19M (76.97%)
ResNet-110 [26]	93.50	252.89M (0.0%)	1.72M (0.0%)
VFP [40]	92.96	160.70M (36.44%)	1.01M (41.27%)
ℓ_1 -norm [10]	93.30	155.0M (38.70%)	1.16M (32.60%)
GAL [66]	92.55	130.20M (48.50%)	0.95M (44.80%)
Ayinde et al. [41]	93.27	154.00M (39.10%)	1.13M (34.20%)
GAL [66]	92.55	130.20M (48.50%)	0.95M (44.80%)
Chen et al. [50]	93.86	126.4M (50.00%)	0.88M (48.91%)
He et al. [52]	93.1	121.1M (52.30%)	–
HBFP-I (Ours)	93.11	119.70M (52.69%)	0.81M (52.66%)
Ding et al. [73]	94.62	105.6M (58.21%)	–
HBFP-II (Ours)	92.91	98.90M (60.89%)	0.67M (41.27%)
Lin et al. [69]	93.71	86.8M (66.0%)	0.53M (69.1%)
HBFP-III (Ours)	92.83	80.20M (68.31%)	0.54M (68.28%)
HRank [36]	92.65	79.30M (68.60%)	0.53M (68.70%)
HBFP-IV (Ours)	91.96	63.30M (74.95%)	0.43M (74.92%)

top-1 accuracy 91.42% with high reduction of FLOPs (78.43%) compared to HRank [36]. However, the proposed method obtains the high FLOPs reduction with comparable performance 91.42% as compared to CFP [60]. Moreover, we achieve a better performance using the proposed HBFP as compared to the reproduced results using CFP [60].

ResNet-110: As per the results summarized in the lower part of Table 3, the filter's ℓ_1 -norm based filter pruning method obtained 93.3% top-1 accuracy by pruning 38.7% of the FLOPs. The recent HRank [36] method achieved 92.65% top-1 performance with 68.6% FLOPs reduction. From Table 3, we can note that our method achieves a 74.95% FLOPs by removing 74.92% of the trainable parameters, with a minimum loss of 1.54% as compared to the baseline using ResNet-110 on CIFAR-10. Moreover, our HBFP-III performs better than HRank [36] in terms of the accuracy with comparable FLOPs reduction.

5.5. Ablation study

In the below section, we provide the ablation study on the effect of the proposed regularizer.

5.6. Effect of regularizer

To investigate the effect of the optimization step, we also conduct the experiments without employing the custom regularizer. We show the effect of the regularizer (optimization step) by comparing the classification results obtained for VGG-16 on CIFAR-10 using the HBFP method with and without employing the regularizer. From Fig. 4, it can be observed that increasing the similarity between the filters belong to a redundant filter pair using a regularizer and thereby training the network decreases the information loss that occurs due to filter pruning.

Table 4

The pruning results of ResNet-50 on ImageNet. The results are arranged in the decreasing order of pruned FLOPs.

Model	Top-1%	Remaining FLOPs (Drop %)	Remaining parameters (Drop %)
Baseline	74.86	3.83B (0.0%)	25.53M (0.0%)
SSS-32 [68]	74.18	2.82B (26.30%)	18.60M (27.10%)
He et al. [9]	72.30	2.73B (28.70%)	–
GAL-0.5 [66]	71.95	2.33B (39.10%)	21.20M (16.90%)
SSS-26 [68]	71.82	2.33B (39.10%)	15.60M (38.80%)
GDP-0.6 [75]	71.19	1.88B (50.90%)	–
Lin et al. [69]	71.11	0.93B (57.3%)	6.90M (55.5%)
GAL-1 [66]	69.88	1.58B (58.70%)	14.60M (42.80%)
GDP-0.5 [75]	69.58	1.57B (59.00%)	–
Ding et al. [73]	76.15	1.45B (62.10%)	–
HBFP-I (Ours)	69.89	1.13B (70.49%)	9.06M (64.50%)
ThinNet-50 [38]	68.42	1.10B (71.27%)	8.66M (66.07%)
HBFP-II (Ours)	69.46	1.06B (72.32%)	8.68M (66.00%)
HBFP-III (Ours)	69.28	0.99B (74.15%)	8.38M (67.17%)
HRank [36]	69.10	0.98B (74.40%)	8.27M (67.60%)
HBFP-IV (Ours)	69.17	0.94B (75.45%)	8.09M (68.30%)

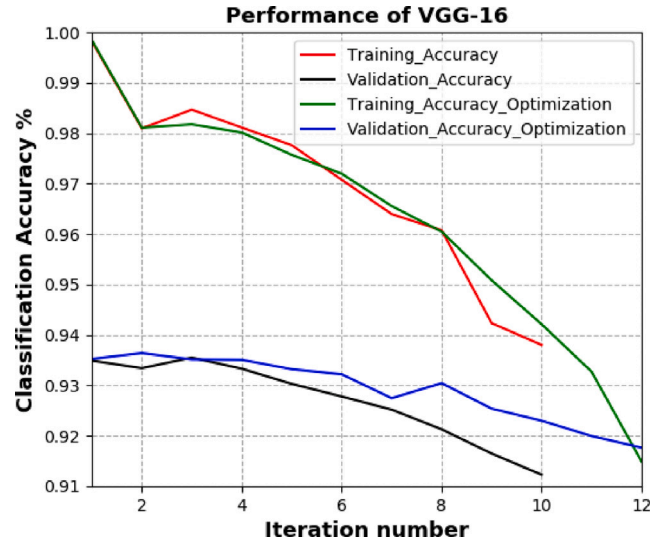


Fig. 4. Illustrating the effect of pruning results obtained using the proposed pruning method with and without employing optimization. We can observe, introducing a custom regularizer to the objective increases the model's performance.

The reason for minimum information loss is that the optimization step increases the redundancy level among the filters of a pair such that removal of one filter does not affect the performance.

5.7. ResNet-50 on ImageNet

The MNIST and CIFAR-10 are medium-scale datasets consisting of low-resolution images. To demonstrate the efficacy of the proposed method over a large-scale dataset having high-resolution images, we also experiment with ImageNet dataset. The pruning results of ResNet-50 on ImageNet is shown in Table 4. Training ResNet-50 with the same parameters as in [26] except batch size produces the top-1 accuracy 74.86%. We consider the batch size as 32 due to computational resource limit (originally the ResNet-50 is trained with batch size 128). From Table 4, we can observe that the proposed HBFP method results in 69.17 top-1 accuracy with 75.45% and 68.3% reduction in FLOPs and parameters, respectively. We can also observe that our method outperforms HRank [36] (second last row) with an increased percentage reduction in FLOPs and Parameters. Thus, it is observed that the HBFP model is also suitable for large-scale datasets having high-resolution images.

6. Conclusion

We propose a new filter pruning technique that uses the filters' information at every epoch during network training. The proposed History Based Filter Pruning (HBFP) method is able to prune a higher percentage of convolution filters compared with state-of-the-art pruning methods. At the same time, HBFP pruning can produce a less error rate. Eventually, it reduces the FLOPs available in LeNet-5 (97.98%), VGG-16 (83.42%), ResNet-56 (78.43%), ResNet-110 (74.95%), ResNet-50 (75.45%) models. The main finding of this paper is to prune the filters that exhibit similar behavior throughout the network training as the removal of one such filter from a filter pair does not affect the model's performance greatly. According to our study, employing the custom regularizer to the objective function also improves the classification results. We show the importance of the proposed pruning strategy through experiments, including LeNet-5 on MNIST, VGG-16/ResNet-56/ResNet-110 on CIFAR-10, and ResNet-50 on ImageNet. It is also observed that the proposed method is robust to low and high-resolution images. One possible direction of future research is pruning the filters further by considering the similarity among the filters from different layers.

CRediT authorship contribution statement

S.H. Shabbeer Basha: Methodology, Conceptualization, Software, Validation, Investigation, Visualization, Writing – original draft. **Mohammad Farazuddin:** Software, Validation, Investigation. **Viswanath Pulabaigari:** Methodology, Writing – review & editing, Project administration, Supervision. **Shiv Ram Dubey:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision. **Snehasis Mukherjee:** Validation, Investigation, Resources, Methodology, Writing, Review, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

We acknowledge the NVIDIA Corporation's support with the donation of GeForce Titan XP GPU, which is helpful in conducting the experiments of this research.

References

- [1] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, *Nature* 521 (7553) (2015) 436–444.
- [2] H.M. Fayek, M. Lech, L. Cavodon, Evaluating deep learning architectures for speech emotion recognition, *Neural Netw.* 92 (2017) 60–68.
- [3] C. Finn, K. Xu, S. Levine, Probabilistic model-agnostic meta-learning, in: *Advances in Neural Information Processing Systems*, 2018, pp. 9516–9527.
- [4] V. Kumar Verma, G. Arora, A. Mishra, P. Rai, Generalized zero-shot learning via synthesized examples, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4281–4289.
- [5] J. Yoon, T. Kim, O. Dia, S. Kim, Y. Bengio, S. Ahn, Bayesian model-agnostic meta-learning, in: *Advances in Neural Information Processing Systems*, 2018, pp. 7332–7342.
- [6] S. Han, H. Mao, W.J. Dally, Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding, 2015, arXiv preprint arXiv:1510.00149.
- [7] Z. Wu, T. Nagarajan, A. Kumar, S. Rennie, L.S. Davis, K. Grauman, R. Feris, Blockdrop: Dynamic inference paths in residual networks, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 8817–8826.
- [8] E.L. Denton, W. Zaremba, J. Bruna, Y. LeCun, R. Fergus, Exploiting linear structure within convolutional networks for efficient evaluation, in: *Advances in Neural Information Processing Systems*, 2014, pp. 1269–1277.
- [9] Y. He, X. Zhang, J. Sun, Channel pruning for accelerating very deep neural networks, in: *Proceedings of the IEEE International Conference on Computer Vision*, 2017, pp. 1389–1397.
- [10] H. Li, A. Kadav, I. Durdanovic, H. Samet, H.P. Graf, Pruning filters for efficient convnets, 2016, arXiv preprint arXiv:1608.08710.
- [11] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, 2014, arXiv preprint arXiv:1409.1556.
- [12] T. Liang, J. Glossner, L. Wang, S. Shi, X. Zhang, Pruning and quantization for deep neural network acceleration: A survey, *Neurocomputing* 461 (2021) 370–403.
- [13] W. Chen, J. Wilson, S. Tyree, K. Weinberger, Y. Chen, Compressing neural networks with the hashing trick, in: *International Conference on Machine Learning*, 2015, pp. 2285–2294.
- [14] C. Louizos, K. Ullrich, M. Welling, Bayesian compression for deep learning, in: *Advances in Neural Information Processing Systems*, 2017, pp. 3288–3298.
- [15] M. Rastegari, V. Ordonez, J. Redmon, A. Farhadi, Xnor-net: Imagenet classification using binary convolutional neural networks, in: *European Conference on Computer Vision*, Springer, 2016, pp. 525–542.
- [16] A. Polino, R. Pascanu, D. Alistarh, Model compression via distillation and quantization, 2018, arXiv preprint arXiv:1802.05668.
- [17] Y. Li, S. Gu, L.V. Gool, R. Timofte, Learning filter basis for convolutional neural network compression, in: *Proceedings of the IEEE International Conference on Computer Vision*, 2019, pp. 5623–5632.
- [18] Y. Li, S. Gu, C. Mayer, L.V. Gool, R. Timofte, Group sparsity: The hinge between filter pruning and decomposition for network compression, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 8018–8027.
- [19] R. Abbasi-Asl, B. Yu, Structural compression of convolutional neural networks based on greedy filter pruning, 2017, arXiv preprint arXiv:1705.07356.
- [20] X. Zhang, J. Zou, X. Ming, K. He, J. Sun, Efficient and accurate approximations of nonlinear convolutional networks, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 1984–1992.
- [21] A. Krizhevsky, I. Sutskever, G.E. Hinton, Imagenet classification with deep convolutional neural networks, in: *Advances in Neural Information Processing Systems*, 2012, pp. 1097–1105.
- [22] X. Xie, H. Zhang, J. Wang, Q. Chang, J. Wang, N.R. Pal, Learning optimized structure of neural networks by hidden node pruning with L_1 regularization, *IEEE Trans. Cybern.* 50 (3) (2019) 1333–1346.
- [23] Y. LeCun, J.S. Denker, S.A. Solla, Optimal brain damage, in: *Advances in Neural Information Processing Systems*, 1990, pp. 598–605.
- [24] B. Hassibi, D.G. Stork, Second order derivatives for network pruning: Optimal brain surgeon, in: *Advances in Neural Information Processing Systems*, 1993, pp. 164–171.
- [25] H. Hu, R. Peng, Y.-W. Tai, C.-K. Tang, Network trimming: A data-driven neuron pruning approach towards efficient deep architectures, 2016, arXiv preprint arXiv:1607.03250.
- [26] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 770–778.
- [27] G. Huang, Z. Liu, L. Van Der Maaten, K.Q. Weinberger, Densely connected convolutional networks, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 4700–4708.
- [28] X. Ding, G. Ding, Y. Guo, J. Han, Centripetal SGD for pruning very deep convolutional networks with complicated structure, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4943–4953.
- [29] F. Tung, G. Mori, Clip-q: Deep network compression learning by in-parallel pruning-quantization, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7873–7882.
- [30] H. Miao, A. Li, L.S. Davis, A. Deshpande, Towards unified data and lifecycle management for deep learning, in: *2017 IEEE 33rd International Conference on Data Engineering, ICDE, IEEE*, 2017, pp. 571–582.
- [31] X. Ruan, Y. Liu, C. Yuan, B. Li, W. Hu, Y. Li, S. Maybank, EDP: An efficient decomposition and pruning scheme for convolutional neural network compression, *IEEE Trans. Neural Netw. Learn. Syst.* (2020).
- [32] X. Ma, S. Lin, S. Ye, Z. He, L. Zhang, G. Yuan, S.H. Tan, Z. Li, D. Fan, X. Qian, et al., Non-structured DNN weight pruning—is it beneficial in any platform? *IEEE Trans. Neural Netw. Learn. Syst.* (2021).
- [33] M. Denil, B. Shakibi, L. Dinh, M. Ranzato, N. De Freitas, Predicting parameters in deep learning, in: *Advances in Neural Information Processing Systems*, 2013, pp. 2148–2156.
- [34] S. Lin, R. Ji, C. Chen, D. Tao, J. Luo, Holistic CNN compression via low-rank decomposition with knowledge transfer, *IEEE Trans. Pattern Anal. Mach. Intell.* 41 (12) (2018) 2889–2905.
- [35] H. Salehinejad, S. Valaee, Edropout: Energy-based dropout and pruning of deep neural networks, *IEEE Trans. Neural Netw. Learn. Syst.* (2021).
- [36] M. Lin, R. Ji, Y. Wang, Y. Zhang, B. Zhang, Y. Tian, L. Shao, Hrank: Filter pruning using high-rank feature map, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 1529–1538.

- [37] Y. He, G. Kang, X. Dong, Y. Fu, Y. Yang, Soft filter pruning for accelerating deep convolutional neural networks, 2018, arXiv preprint arXiv:1808.06866.
- [38] J.-H. Luo, J. Wu, W. Lin, Thinet: A filter level pruning method for deep neural network compression, in: Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 5058–5066.
- [39] X. Zhang, W. Xie, Y. Li, J. Lei, Q. Du, Filter pruning via learned representation median in the frequency domain, IEEE Trans. Cybern. (2021).
- [40] C. Zhao, B. Ni, J. Zhang, Q. Zhao, W. Zhang, Q. Tian, Variational convolutional neural network pruning, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 2780–2789.
- [41] B.O. Ayinde, T. Inanc, J.M. Zurada, Redundant feature pruning for accelerated inference in deep neural networks, Neural Netw. 118 (2019) 148–158.
- [42] X. Ding, G. Ding, J. Han, S. Tang, Auto-balanced filter pruning for efficient convolutional neural networks, in: Thirty-Second AAAI Conference on Artificial Intelligence, 2018.
- [43] P. Molchanov, S. Tyree, T. Karras, T. Aila, J. Kautz, Pruning convolutional neural networks for resource efficient inference, 2016, arXiv preprint arXiv:1611.06440.
- [44] M. Jaderberg, A. Vedaldi, A. Zisserman, Speeding up convolutional neural networks with low rank expansions, 2014, arXiv preprint arXiv:1405.3866.
- [45] V. Lebedev, V. Lempitsky, Fast convnets using group-wise brain damage, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2554–2564.
- [46] W. Wen, C. Wu, Y. Wang, Y. Chen, H. Li, Learning structured sparsity in deep neural networks, in: Advances in Neural Information Processing Systems, 2016, pp. 2074–2082.
- [47] H. Zhou, J.M. Alvarez, F. Porikli, Less is more: Towards compact cnns, in: European Conference on Computer Vision, Springer, 2016, pp. 662–677.
- [48] J.M. Alvarez, M. Salzmann, Learning the number of neurons in deep networks, in: Advances in Neural Information Processing Systems, 2016, pp. 2270–2278.
- [49] T. Zhang, S. Ye, X. Feng, X. Ma, K. Zhang, Z. Li, J. Tang, S. Liu, X. Lin, Y. Liu, et al., StructADMM: Achieving ultrahigh efficiency in structured pruning for DNNs, IEEE Trans. Neural Netw. Learn. Syst. (2021).
- [50] Z. Chen, T.-B. Xu, C. Du, C.-L. Liu, H. He, Dynamical channel pruning by conditional accuracy change for deep neural networks, IEEE Trans. Neural Netw. Learn. Syst. (2020).
- [51] X. Song, Y. Chen, Z.-H. Feng, G. Hu, D.-J. Yu, X.-J. Wu, SP-GAN: Self-growing and pruning generative adversarial networks, IEEE Trans. Neural Netw. Learn. Syst. (2020).
- [52] Y. He, X. Dong, G. Kang, Y. Fu, C. Yan, Y. Yang, Asymptotic soft filter pruning for deep convolutional neural networks, IEEE Trans. Cybern. 50 (8) (2019) 3594–3604.
- [53] J. Wang, T. Jiang, Z. Cui, Z. Cao, Filter pruning with a feature map entropy importance criterion for convolution neural networks compressing, Neurocomputing 461 (2021) 41–54.
- [54] J. Gou, B. Yu, S.J. Maybank, D. Tao, Knowledge distillation: A survey, Int. J. Comput. Vis. (2021) 1–31.
- [55] G. Kyriakides, K. Margaritis, An introduction to neural architecture search for convolutional networks, 2020, arXiv preprint arXiv:2005.11074.
- [56] M. Lin, R. Ji, Y. Zhang, B. Zhang, Y. Wu, Y. Tian, Channel pruning via automatic structure search, 2020, arXiv preprint arXiv:2001.08565.
- [57] Z. Liu, H. Mu, X. Zhang, Z. Guo, X. Yang, K.-T. Cheng, J. Sun, Metapruning: Meta learning for automatic neural network channel pruning, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 3296–3305.
- [58] M.U. Haider, M. Taj, Comprehensive online network pruning via learnable scaling factors, in: 2021 IEEE International Conference on Image Processing, ICIP, IEEE, 2021, pp. 3557–3561.
- [59] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, et al., Gradient-based learning applied to document recognition, Proc. IEEE 86 (11) (1998) 2278–2324.
- [60] P. Singh, V.K. Verma, P. Rai, V. Nambodiri, Leveraging filter correlations for deep model compression, in: The IEEE Winter Conference on Applications of Computer Vision, 2020, pp. 835–844.
- [61] Y. LeCun, C. Cortes, C. Burges, MNIST handwritten digit database, 2010, p. 2, ATT Labs [Online]. Available: <http://yann.lecun.com/exdb/mnist>.
- [62] A. Krizhevsky, G. Hinton, et al., Learning multiple layers of features from tiny images, 2009.
- [63] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, Imagenet: A large-scale hierarchical image database, in: 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, 2009, pp. 248–255.
- [64] D. Molchanov, A. Ashukha, D. Vetrov, Variational dropout sparsifies deep neural networks, in: Proceedings of the 34th International Conference on Machine Learning-Volume 70, JMLR. org, 2017, pp. 2498–2507.
- [65] K. Neklyudov, D. Molchanov, A. Ashukha, D.P. Vetrov, Structured bayesian pruning via log-normal multiplicative noise, in: Advances in Neural Information Processing Systems, 2017, pp. 6775–6784.
- [66] S. Lin, R. Ji, C. Yan, B. Zhang, L. Cao, Q. Ye, F. Huang, D. Doermann, Towards optimal structured cnn pruning via generative adversarial learning, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 2790–2799.
- [67] Y. He, P. Liu, Z. Wang, Z. Hu, Y. Yang, Filter pruning via geometric median for deep convolutional neural networks acceleration, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 4340–4349.
- [68] Z. Huang, N. Wang, Data-driven sparse structure selection for deep neural networks, in: Proceedings of the European Conference on Computer Vision, ECCV, 2018, pp. 304–320.
- [69] M. Lin, L. Cao, Y. Zhang, L. Shao, C.-W. Lin, R. Ji, Pruning networks with cross-layer ranking & k-reciprocal nearest filters, IEEE Trans. Neural Netw. Learn. Syst. (2022).
- [70] R. Yu, A. Li, C.-F. Chen, J.-H. Lai, V.I. Morariu, X. Han, M. Gao, C.-Y. Lin, L.S. Davis, Nisp: Pruning networks using neuron importance score propagation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 9194–9203.
- [71] Y. He, J. Lin, Z. Liu, H. Wang, L.-J. Li, S. Han, Amc: Automl for model compression and acceleration on mobile devices, in: Proceedings of the European Conference on Computer Vision, ECCV, 2018, pp. 784–800.
- [72] K. Zhang, G. Liu, M. Lv, RUFF: Reinitializing unimportant filters for soft pruning, Neurocomputing 483 (2022) 311–321.
- [73] X. Ding, T. Hao, J. Tan, J. Liu, J. Han, Y. Guo, G. Ding, Resrep: Lossless cnn pruning via decoupling remembering and forgetting, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 4510–4520.
- [74] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, 2015, arXiv preprint arXiv:1502.03167.
- [75] S. Lin, R. Ji, Y. Li, Y. Wu, F. Huang, B. Zhang, Accelerating convolutional networks via global & dynamic filter pruning, in: IJCAI, 2018, pp. 2425–2432.



S.H. Shabbeer Basha is currently associated with RV University Bangalore as an Associate Professor. Before joining RV University, he worked as a Machine Learning Scientist at Lytx India. He received the Ph.D. degree in Computer Science and Engineering from Indian Institute of Information Technology Sri City (IIITS). His research interests include Computer Vision, Deep Learning, Deep Model Compression, Unsupervised Domain Adaptation, Transfer Learning, and Multi-Task Learning. He is actively serving as reviewer for many journals like IEEE Transactions on Neural Networks and Learning Systems, Neural Networks, Neurocomputing (Elsevier) and conferences like WACV, CVMI, ICCV.



Mohammad Farazuddin has recently completed his M.S. from San Jose State University, US. He has worked as an intern at Ericsson India, Ciphense. Before this he completed his B.Tech. from Indian Institute of Information Technology Sri City. His research interests include Neural Network Compression, Deep Learning, and Computer Vision.



Viswanath Pulabaigari has received his Ph.D. from Indian Institute of Science (IISc) Bangalore. He has obtained B.Tech. from Sri Venkateswara University, Tirupati and M.Tech. from Indian Institute of Technology (IIT) Madras. Currently, he is working as an Associate Professor in the Computer Vision and Machine Learning group at Indian Institute of Information Technology SriCity (IIIT SriCity). He has written several peer-reviewed research papers (in reputed journals and conferences). His research area includes Machine Learning, Computer Vision, Pattern Recognition, and Data Mining.



Shiv Ram Dubey has been with the Indian Institute of Information Technology (IIIT), Allahabad since July 2021, where he is currently the Assistant Professor of Information Technology. He was with IIIT Sri City as Assistant Professor from Dec 2016 to July 2021 and Research Scientist from June 2016 to Dec 2016. He received the Ph.D. degree from IIIT Allahabad in 2016. Before that, from 2012 to 2013, he was a Project Officer at Indian Institute of Technology (IIT), Madras. He was a recipient of several awards including Best Ph.D. Award in Ph.D. Symposium at IEEE-CICT2017, Early Career Research Award from SERB, Govt. of India and NVIDIA GPU Grant Award Twice from NVIDIA. His research interest includes Computer Vision and Deep Learning.



Snehasis Mukherjee is an Assistant Professor at Shiv Nadar University, Delhi NCR, India since May 2020. He obtained his Ph.D. in Computer Science from Indian Statistical Institute in 2012. He worked as a Post Doctoral Fellow at NIST, Gaithersburg, USA. Then he spent 6 years as an Assistant Professor at IIIT Sri City till April 2020. He has authored several peer-reviewed research papers in reputed journals and conferences. Snehasis is an Associate Editor of the Springer journal of SN Computer Science. He is an active reviewer of several reputed journals such as IEEE Trans.

NNLS, IEEE Trans. CSVT, IEEE Trans. IP, IEEE Trans. ETCI, IEEE Trans. HMS, IEEE Trans. Cyb, IEEE CIM, CVIU, Pattern Recognition, Neural Networks, Neurocomputing, and many more. He chaired sessions in several prestigious conferences such as ICARCV, ICVGIP and NCVPRIPG. His research area includes Computer Vision, Machine Learning, Image Processing and Graphics.