MDMLP: Image Classification from Scratch on Small Datasets with MLP

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Abstract

The attention mechanism has become a go-to technique for natural language processing and computer vision tasks. Recently, the MLP-Mixer and other MLP-based architectures, based simply on multi-layer perceptrons (MLPs), are also powerful compared to CNNs and attention techniques and raises a new research direction. However, the high capability of the MLP-based networks severely relies on large volume of training data, and lacks of explanation ability compared to the Vision Transformer (ViT) or ConvNets. When trained on small datasets, they usually achieved inferior results than ConvNets. To resolve it, we present (i) multi-dimensional MLP (MDMLP), a conceptually simple and lightweight MLP-based architecture yet achieves SOTA when training from scratch on small-size datasets; (ii) multi-dimension MLP Attention Tool (MDAttnTool), a novel and efficient attention mechanism based on MLPs. Even without strong data augmentation, MDMLP achieves 90.90% accuracy on CIFAR10 with only 0.3M parameters, while the well-known MLP-Mixer achieves 85.45% with 17.1M parameters. In addition, the lightweight MDAttnTool highlights objects in images, indicating its explanation power. Our code is available at https://github.com/Amoza-Theodore/MDMLP.

1 Introduction

Transformer [1] with attention mechanism has become the dominant architecture in natural language processing (NLP). As a successful application of the attention mechanism to the computer vision (CV), Vision Transformer (ViT), and its variations [2–6], has gained popularity in many fields. Lately, the MLP-Mixer model [7], which is purely based on multi-layer perceptrons (MLPs), has achieved a powerful performance compared to state-of-the-art architectures, demonstrating a new probable research trend. However, there are still many problems to be resolved.

First, MLP-Mixer and its variations [7–13] encode spatial information by flattening the spatial dimensions to the channel dimension (i.e. reshaped to "tokens×channels"), resulting in the loss of positional and channel information. The Vision Permutator (ViP) [8], which is closest to our work, splits image to non-overlapping patches and permutes along height, width, and channel to apply MLP. However, this loses relation and continuity information between patches. Imaging pixels around a split boundary are highly correlated and continuous, but the model has no clue about it after splitting.

Second, MLP-Mixer requires an immense amount of training dataset (14M-300M images), suffering the dilemma which cannot be trained in mid-size (1-10M images) or small-size datasets from scratch, and existing MLP models [14–17] have low accuracy for small-size datasets, compared to ConvNets. There has been a lot of work [12, 10, 18] that attempts to apply the MLP architecture to mid-size
datasets. For small-size datasets, however, only the vision transformer variant [19] achieves fairly good results compared to ConvNets like ResNet. Although transfer learning is a good therapy for small-size datasets, on largely shifted domains, it may not be effective. It remains a problem whether MLP-based architecture can be trained well from scratch on a small-size dataset.

Third, MLP-Mixer uses non-overlap patch embedding, which loses potential positional information. Much work [20–23] has been done to explore this phenomenon. Our experiment has shown that the use of overlapped patches significantly improves performance by approximately 3%.

Fourth, MLP-Mixer lacks an effective means of explanation. For ViT, attention visualization and interpretability [24] are important factors in its success, but for MLP-Mixer and similar methods, it’s unclear what are learned from training. EAMLP [25] uses linear layers to realize the multi-attention mechanism, but this is not a general approach (as applied to ConvNets) and is still limited to the self-attention mechanism.

In view of the above problems, we propose an efficient architecture called multi-dim MLP (MDMLP). It accepts a sequence of linearly projected image patches (i.e. tokens) with overlap as input, keeping its dimensionality for not losing any information. MDMLP uses four types of MLP layers: height-mixing, width-mixing, channel-mixing, and token-mixing MLPs with normalization. In addition, for
visualization, we propose a multi-dim MLP Attention Tool (MDAttnTool). It consists of two layers of MLPs with eight hidden units and an average pooling layer to get weights.

Despite its simplicity, MDMLP with MDAttnTool has achieved excellent performance. Without strong augmentations, MDMLP achieves 90.90% on CIFAR10 along with 0.30M parameters and 0.28G flops, while MLP-Mixer [11] can only achieve 85.45% together with 17.1M parameters and 1.21G flops, and Neyshabur’s model [14] only achieves 85.19%. MDAttnTool successfully visualizes the attention area as well as the object boundary not only on MDMLP but also on ResNet [26], which proved to be a general visualization method, breaking through the existing self-attention mechanism.

In summary, our contributions are as follows:

- We propose multi-dim MLP (MDMLP) to train from scratch on small-size datasets and gain the highest accuracy, with yet extremely low parameters and flops which are comparable to ConvNets.
- We propose overlap patch embedding to make up for the loss of adjacent information caused by the split of neighboring image blocks.
- We propose MLP Attention Tool (MLPAttnTool) to visualize the feature learned by the neural network, which is a general tool applicable not only to our model but also to other models such as ConvNets.

2 Related Works

Much of the work has concentrated on pure MLP architectures on small-size datasets such as CIFAR10 [27], but not nearly as accurate as ours. Various works [16, 17] are committed to making MLP competitive with state-of-the-art models. Lin et al. [15] used fully connected networks together with heavy data augmentation and pre-training, achieving 70% accuracy on CIFAR10. Tolstikhin et al. [7] worked out the MLP-Mixer, attaining approximately 80% accuracy on CIFAR10 if trained from scratch. Neyshabur [14] developed an MLP architecture with a regularizer constraining the model to be close to networks based on conv and get 85.19% accuracy on CIFAR10. Our work, MDMLP, conceptually simple and extremely light in the terms of parameters and flops but reaches high accuracy without heavy augmentations (mixup, cutmix, etc.).

Pure MLP architectures have thrived on large-size datasets (14M-300M images, such as JFT-300M [28]) and mid-size datasets (1-10M images, such as IMAGENET-1K [29]) with heavy augmentations, but have yet to overcome small datasets. The MLP-Mixer [7] successfully achieves state-of-the-art performance on large-size datasets. Plenty of works [12, 9, 8, 10, 8, 30] are successful with mid-size datasets in Image Classification. Other work [11, 13, 31] demonstrates that the pure MLP architecture can also gain fantastic performance in Object Detection and Semantic Segmentation. Hou et al. [8] brought up the Vision Permutator with height and width dimensions, much similar to our work which keeping height, width and channel dimensions. By comparison, Our work focus on small-size datasets without heavy augmentations, CIFAR10, CIFAR100, Flowers102, and so on.

The work of attention mechanism [1] in computer vision [2] makes "Patch Embed" a core module in model design field. Cordonnier et al. [32] extracted $2 \times 2$ patches from the input image (referred as "Patch Embed") and applied self-attention layers on CIFAR10. Also, a lot of ViT variants [3–6] prove the excellent performance of ViT on large-size and mid-size image classification datasets, Object Detection and Semantic Segmentation. Other work [33, 34] center on Unsupervised learning and transfer learning. Lee et al. [19] put forward shift layer to make ViT success in small-size datasets. Yu et al. [35] advised that the attention component is not necessary in transformer block. Our work use overlap patch embedding (i.e. split patch with overlap pixels) greatly improving our model’s performance.

Many have attempted to make attention mechanism and MLP architecture explainable. Vision transformer [19] itself has visualized attention layer and positional embeddings. Chefer et al. [24] visualize attention layer in an image more clearly. Hao et al. [36] visualize attention layer in words and explain the inner properties. Touvron et al. [12] visualize the MLP’s positional embeddings. In our work, we use a 2-layer fully connected network with 8 hidden units as a new attention add-on to visualize the MLP’s learned representations, successfully draw the attention area and the object boundary.
The model design field is full of vitality, to some degree, by modern training strategies and data augmentations methods. He et al. [26] developed residual connection, to handle the problem of gradient disappearance. Ba et al. [37] raised layer norm, making it possible to norm data of different shapes. Moreover, [38] and Liu et al. [39] use modern model design approaches, making the out-of-date convnet comes alive again. The Pytorch [40], timm [41] and einops library [42] provide a lot of add-ons for data augmentations and processing such as mixup [43], cutmix [44], label smoothing [45], random erase [46], EMA [47], stochastic depth [48], AutoAugment [49], RandAugment [50]. But our work concentrate on lightweight the model, we do not use strong augmentation in our training regime in terms of this.

3 MDMLP Architecture

Figure 1 shows the overall architecture of MDMLP. In a nutshell, MDMLP accepts a sequence of overlapped patch embeddings maintaining the height, width, channels and base-dim dimensions without losing any information. Then, it applies N layers of MDBlocks, each of which consists of FC layers applied to each dimension of those patches in turn. Last, it utilizes a standard classification head, global average pooling and linear classifier.

3.1 Overlap Patch Embedding

ViTs [19] has introduced Patch Embed, which splits images into patches followed by a linear layer to map patches to tokens, but without overlap. Essentially, non-overlap patch embedding can be replaced by a convolution operation where stride is equal to kernel size. But for traditional Convolutional Neural Networks (CNNs), it is common that stride is smaller than kernel size, i.e. with overlap. Inspired by this, in MDMLP, we also use overlap patch embedding to obtain the neighboring information between connected patches.

The calculation of overlap patch embedding is the same as the convolution operation.

\[
\begin{align*}
\mathbb{R}^{C \times H \times W} & \xrightarrow{\text{Overlap Patch Split}} \mathbb{R}^{H' \times W' \times C \times P} \\
\mathbb{R}^{H' \times W' \times C \times P} & \xrightarrow{\text{Patch Embedding}} \mathbb{R}^{H' \times W' \times C \times D}
\end{align*}
\]

where the second mapping is a linear embedding layer, \( P \) is the patch size, \( O \) is the overlap size.

The overlap patch embedding, to some extent, provides not only positional information but also a larger receptive field.

3.2 MDBlock

Vision Permutator [8] keeps the dimension of height, width and channel (hwc), and MDMLP maintains the dimension of height, width, channels and base-dim (also referred as "token") dimensions (hwcd). The advantage of this is not losing any dimensional information and saving memory to a large extent.

Multi-dim Block (MDBlock) consists of four Multi-dim Layers (MDLayers) mixing height, width, channel and base-dim (token) information. When an image has been mapped to overlapped patch embeddings in space \( \mathbb{R}^{H' \times W' \times C \times D} \), we then apply \( N \times \) Blocks following a Global Average Pooling layer to get the result of class.

3.3 MDLayer

As the core component of MDMLP, it is composed of transpose and linear layers. Take the Height MDLayer for example, we firstly apply a Layernorm, then arrange (also referred as "transpose") it to \( \mathbb{R}^{D \times W' \times C \times H'} \) followed by an MLP add-on which consists of 2 layers of MLP. We set the
hidden units to $H' \times f$ where $f$ is called expansion factor. GELU activation and dropout have been employed in the MLP layer. Afterwards, we rearrange it to the original shape $\mathbb{R}^{H' \times W' \times C \times D}$ with a self-learning residual connection.

MLP can be formulated as follows (not showing bias and dropout):

$$MLP(X) = X + \sigma(W_2\sigma(W_1X))$$
where $W_1 \in \mathbb{R}^{(f \times n) \times n}, W_2 \in \mathbb{R}^{n \times (f \times n)}$ \hfill (2)

MDLayer can be expressed as follows (Height MDLayer for example):

$$X_0 = \text{LayerNorm}(X)$$

$$X_0 \in \mathbb{R}^{H' \times W' \times C \times D} \xrightarrow{\text{transpose}} X'_0 \in \mathbb{R}^{D \times W' \times C \times H'}$$

$$Y_0 = MLP(X'_0), X'_0 \in \mathbb{R}^{D \times W' \times C \times H'}$$

$$Y_0 \in \mathbb{R}^{D \times W' \times C \times H'} \xrightarrow{\text{transpose}} Y'_0 \in \mathbb{R}^{H' \times W' \times C \times D}$$

$$Y \leftarrow Y'_0 + X, X \in \mathbb{R}^{H' \times W' \times C \times D}$$ \hfill (3)

4 Experiments

In this section, several experiments are conducted to verify that the proposed method improves the performance of MLP architecture in terms of parameters, flops and accuracy. Sec. 4.1 describes the experiment setup. Section 4.2 shows quantitatively that the proposed method effectively improves the MLP architecture and achieves performance comparable to CNN.

4.1 Settings

4.1.1 Environment and Dataset

The proposed method was implemented in Pytorch [40]. CIFAR-10, CIFAR-100 [27], Flowers-102 [51] and Food101 [52] were employed in our experiments whose image size was resized to 224, and the GPU was V100 [53].

4.1.2 Model Configurations

In the case of MDMLP, the configuration was determined experimentally. The hidden dimension was set to 64, the depth was set to 8, the expansion factor ($f$) was set to 4. The patch size was set to 4, the overlap size was set to 2 on CIFAR-10 and CIFAR-100 datasets, while the patch size was set to 14, the overlap size was set to 7 on Flowers102 and Food101 datasets.

For ResNet20, we use ResNet [26] without making any changes. It is worth mentioning that we adopt the implementation of Idelbayev [54] instead of timm [41] whose parameters and flops are one hundred times greater than the former.

In other cases, the tiny model configurations presented in the corresponding papers were adopted as they were respectively considering the trade-off among parameters, flops and accuracy except that the patch size was determined experimentally. For ViT [2], the hidden dimension was set to 192, mlp ratio to 2, depth to 9, heads to 12, patch size to 4 on CIFAR-10 and CIFAR-100 as well as 14 on Flowers102 and Food101. For AS-MLP [11], embed dimension to 96, depth to [2, 2, 6, 2], shift size to 5, patch size to 2 on CIFAR-10 and CIFAR-100 as well as 7 on Flowers102 and Food101. For gMLP [9], number of blocks to 30, embed dimension to 128, mlp ratio to 6, patch size to 4 on CIFAR-10 and CIFAR-100 as well as 14 on Flowers102 and Food101. For ResMLP [12], number of blocks to 12, embed dimension to 384, mlp ratio to 4, patch size to 4 on CIFAR-10 and CIFAR-100 as well as 28 on Flowers102 and Food101. For ViP [8], number of layers to [4, 3, 8, 3], mlp ratio to 3, embed dimension to 384, the patch size to 4 on CIFAR-10 and CIFAR-100 as well as 28 on Flowers102 and Food101. For MLP-Mixer [7], number of blocks to 8, embed dimension to 512, patch size to 4 on CIFAR-10 and CIFAR-100 as well as 14 on Flowers102 and Food101. For S-FC ($\beta$-LASSO), the result was from the corresponding paper [14].
### Table 1: Experiments on CIFAR-10 and CIFAR-100

| FAMILY | MODEL      | PARAMS (M) | FLOPS (G) | ACC (%) |
|--------|------------|------------|-----------|---------|
|        |            | CIFAR10    | CIFAR100  |         |
| Conv   | ResNet20   | 0.27       | 0.04      | 91.99   | 67.39   |
| Trans  | ViT        | 2.69       | 0.19      | 86.57   | 60.43   |
| MLP    | AS-MLP     | 26.20      | 0.33      | 87.30   | 65.16   |
| MLP    | gMLP       | 4.61       | 0.34      | 86.79   | 61.60   |
| MLP    | ResMLP     | 14.30      | 0.93      | 86.52   | 61.40   |
| MLP    | ViP        | 29.30      | 1.17      | 88.97   | **70.51** |
| MLP    | MLP-Mixer  | 17.10      | 1.21      | 85.45   | 55.06   |
| MLP    | S-FC ($\beta$-LASSO) | -          | -         | 85.19   | 59.56   |
| MLP    | MDMLP (ours) | 0.30       | 0.28      | 90.90   | 64.22   |

### Table 2: Experiments on FLOWERS102 and FOOD101

| FAMILY | MODEL      | PARAMS (M) | FLOPS (G) | ACC (%) |
|--------|------------|------------|-----------|---------|
|        |            | FLOWERS102 | FOOD101   |         |
| Conv   | ResNet20   | 0.28       | 2.03      | 57.94   | 74.91   |
| Trans  | ViT        | 2.85       | 0.94      | 50.69   | 66.41   |
| MLP    | AS-MLP     | 26.30      | 1.33      | 48.92   | 74.92   |
| MLP    | gMLP       | 6.54       | 1.93      | 47.35   | 73.56   |
| MLP    | ResMLP     | 14.99      | 1.23      | 45.00   | 68.40   |
| MLP    | ViP        | 30.22      | 1.76      | 42.16   | 69.91   |
| MLP    | MLP-Mixer  | 18.20      | 4.92      | 49.41   | 61.86   |
| MLP    | MDMLP (ours) | 0.41       | 1.59      | **60.39** | **77.85** |

### 4.1.3 Training Regime

We do not use any strong augmentations or regularization techniques in all training configurations contrary to other papers, i.e., cutmix, auto augment, label smoothing, etc. What we only use are horizontal flip and color jitter.

The training strategy was adopted from ResNet [26] without any changes based on experiments. The SGD [55] was used as the optimizer. Weight decay was set to 0.0001, batch size to 128 (however, 16 for flowers102), and warm-up to 10. All models were trained for 200 epochs, the cosine learning rate decay was used, and the initial learning rate was set to 0.1. All the training was done on timm [41].

### 4.2 Quantitative Result

#### 4.2.1 Image Classification

This section presents the experimental results for small-size datasets.

As showed in Table 1 On CIFAR10 and CIFAR100 datasets, our model achieves the significant reduction of parameters and flops under the competitive accuracy. MDMLP achieves the best accuracy of 90.90% among all MLP and Transformer model families on CIFAR10 with the 0.30M parameters which is at least ten times smaller than others, achieving the comparable performance with ConvNets in terms of parameters, flops and accuracy.

Moreover, on flowers102 and food101 datasets (Table 2), our model beats all other models in all three metrics ways. MDMLP achieves 60.39% and 77.85% respectively on flowers102 and food101, with 0.41M parameters and 1.59G flops.
### Table 3: Ablation Study on CIFAR-10 and CIFAR-100

| MODEL                        | CIFAR10 | CIFAR100 |
|------------------------------|---------|----------|
| MDMLP (ours)                 | 90.90   | 64.22    |
| – overlap                    | 88.87   | 60.95    |
| – mdblock                    | 87.09   | 57.08    |
| – overlap, mdblock (MLP-Mixer)| 85.45   | 55.06    |

#### 4.2.2 Ablation Study

This section shows that both our MDBlock and overlap patch embedding method play significant roles in the MDMLP model.

On one hand, the overlap patch embedding method, which provides more information between patches, improves the accuracy by 2% and 4% respectively on cifar10 and cifar100 datasets. We attribute this to the elevation of the receptive field.

On the other hand, the MDBlock architecture contributes to the whole performance by 3.8% on CIFAR10 and 7.1% on CIFAR100. Further, if both MDBlock and overlap patch embedding components are removed, our MDMLP model is essentially MLP-Mixer and the prediction accuracy drops again.

#### 5 MDAttnTool for Visualization

ViT and its variants [19] has shown the attention values in visualization attributed to the attention layer, so we arise an MLP based attention layer for visualization. The Multi-dim Attention Layer (MDAttnTool) consists of 2 layers where the number of hidden units is 8, as the same to MLP layer (formula 2) but different in Global Average Pooling layer.

**MLP in MDAttnTool can be written as follows.** (not shown bias and dropout)

\[
MLP(X) = X + \sigma(W_2\sigma(W_1\text{Norm}(X)))
\]

\[
W_1 \in \mathbb{R}^{m \times n}, \quad W_2 \in \mathbb{R}^{n \times m}
\]  

(4)
MD Attention Tool

Figure 3: MDAttnTool. The input was transposed to "B C H W" followed by an MLP Layer and then transposed to "B C W H" to get the Height features. Then with a Global Average Pooling getting the weights which will be elementwise produced to the input.

**MDAttnTool for Image can be written as follows.**

\[ Y_1 = MLP_w(X), X \in \mathbb{R}^{C \times H \times W} \]
\[ Y_1 \in \mathbb{R}^{C \times H \times W} \xrightarrow{\text{transpose}} Y'_1 \in \mathbb{R}^{C \times W \times H} \]
\[ Y_2 = MLP_h(Y'_1), Y'_1 \in \mathbb{R}^{C \times W \times H} \]
\[ Y_2 \in \mathbb{R}^{C \times W \times H} \xrightarrow{\text{transpose}} Y'_2 \in \mathbb{R}^{C \times H \times W} \]
\[ V = \text{AvgPool}(Y'_2), \mathbb{R}^{C \times H \times W} \xrightarrow{\text{transpose}} \mathbb{R}^{1 \times H \times W} \]
\[ Y = V \odot X \]

(5)

where AvgPool is referred to "Global Average Pooling", and V (also referred to as "weights") are initialized to 1.0 at the beginning.

Multi-dim MLP Attention Tool has successfully shown the learned features in Figure 2, which contains not only attention but also some positional information (shown as object boundary). By the way, the pure MLP based attention architecture is extremely light compared to Vision Transformer [19].

In addition, MDAttnTool breaks through the existing self-attention mechanism compared to EAMLP [25]. Though EAMLP uses pure MLP architecture to get the attention, our method use elementwise product replacing the self-attention mechanism.

### 6 Conclusion and Future Work

To explore whether MLP-based architecture can achieve great visual recognition results when training on small datasets from scratch just as ConvNets, we propose MDMLP, which takes up to ten times smaller parameters than the existing MLP models. To visualize the model, we propose MDAttnTool, which is a general method to highlight the attention of models. However, one limitation is that the
throughput is not as expected compared to our good-performing FLOPs. Although the current model still cannot outperform SOTA results on all datasets, we hope this work open a door to more revisits of MLP architectures in small-scale datasets for visual recognition tasks.

References

[1] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in neural information processing systems, 30, 2017.

[2] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. International Conference on Learning Representations, 2021.

[3] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10012–10022, 2021.

[4] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In International Conference on Machine Learning, pages 10347–10357. PMLR, 2021.

[5] Hangbo Bao, Li Dong, and Furu Wei. Beit: Bert pre-training of image transformers. arXiv preprint arXiv:2106.08254, 2021.

[6] Wenhao Wang, Enze Xie, Xiang Li, Deng-Ping Fan, Kaitao Song, Ding Liang, Tong Lu, Ping Luo, and Ling Shao. Pyramid vision transformer: A versatile backbone for dense prediction without convolutions. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 568–578, 2021.

[7] Ilya O Tolstikhin, Neil Houlsby, Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Thomas Unterthiner, Jessica Yung, Andreas Steiner, Daniel Keysers, Jakob Uszkoreit, et al. Mlp-mixer: An all-mlp architecture for vision. Advances in Neural Information Processing Systems, 34, 2021.

[8] Qibin Hou, Zihang Jiang, Li Yuan, Ming-Ming Cheng, Shuicheng Yan, and Jiashi Feng. Vision permutator: A permutable mlp-like architecture for visual recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2022.

[9] Hanxiao Liu, Zihang Dai, David So, and Quoc Le. Pay attention to mlps. Advances in Neural Information Processing Systems, 34, 2021.

[10] Yehui Tang, Kai Han, Jianyuan Guo, Chang Xu, Yanxi Li, Chao Xu, and Yunhe Wang. An image patch is a wave: Phase-aware vision mlp. Conference on Computer Vision and Pattern Recognition, 2021.

[11] Dongze Lian, Zehao Yu, Xing Sun, and Shenghua Gao. As-mlp: An axial shifted mlp architecture for vision. arXiv preprint arXiv:2107.10224, 2021.

[12] Behnam Neyshabur. Towards learning convolutions from scratch. Advances in Neural Information Processing Systems, 33:8078–8088, 2020.

[13] Zhouhan Lin, Roland Memisevic, and Kishore Konda. How far can we go without convolution: Improving fully-connected networks. ICLR, Workshop Track, 2016.

[14] Decebal Constantin Mocanu, Elena Mocanu, Peter Stone, Phuong H Nguyen, Madeleine Gibescu, and Antonio Liotta. Scalable training of artificial neural networks with adaptive sparse connectivity inspired by network science. Nature communications, 9(1):1–12, 2018.

[15] Gregor Urban, Krzysztof J Geras, Samira Ebrahimi Kahou, Ozlem Aslan, Shengjie Wang, Rich Caruana, Abdelrahman Mohamed, Matthai Philipose, and Matt Richardson. Do deep convolutional nets really need to be deep and convolutional? International Conference on Learning Representations, 2017.
[18] Jiachen Li, Ali Hassani, Steven Walton, and Humphrey Shi. Convmlp: Hierarchical convolutional mlps for vision. arXiv preprint arXiv:2109.04454, 2021.

[19] Seung Hoon Lee, Seunghyun Lee, and Byung Cheol Song. Vision transformer for small-size datasets. arXiv preprint arXiv:2112.13492, 2021.

[20] Asher Trockman and J Zico Kolter. Patches are all you need? arXiv preprint arXiv:2201.09792, 2022.

[21] Li Yuan, Yunpeng Chen, Tao Wang, Weihao Yu, Yujun Shi, Zi-Hang Jiang, Francis EH Tay, Jiashi Feng, and Shuicheng Yan. Tokens-to-token vit: Training vision transformers from scratch on imagenet. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 558–567, 2021.

[22] Tete Xiao, Piotr Dollar, Mannat Singh, Eric Mintun, Trevor Darrell, and Ross Girshick. Early convolutions help transformers see better. Advances in Neural Information Processing Systems, 34, 2021.

[23] Kun Yuan, Shaopeng Guo, Ziwei Liu, Aojun Zhou, Fengwei Yu, and Wei Wu. Incorporating convolution designs into visual transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 579–588, 2021.

[24] Hila Chefer, Shir Gur, and Lior Wolf. Transformer interpretability beyond attention visualization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 782–791, 2021.

[25] Meng-Hao Guo, Zheng-Ning Liu, Tai-Jiang Mu, and Shi-Min Hu. Beyond self-attention: External attention using two linear layers for visual tasks. arXiv preprint arXiv:2105.02358, 2021.

[26] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[27] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

[28] Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta. Revisiting unreasonable effectiveness of data in deep learning era. In Proceedings of the IEEE international conference on computer vision, pages 843–852, 2017.

[29] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009.

[30] Xiaohan Ding, Chunlong Xia, Xiangyu Zhang, Xiaojie Chu, Jungong Han, and Guiguang Ding. Repmlp: Re-parameterizing convolutions into fully-connected layers for image recognition. arXiv preprint arXiv:2105.01883, 2021.

[31] Jianyuan Guo, Yehui Tang, Kai Han, Xinghao Chen, Han Wu, Chao Xu, Chang Xu, and Yunhe Wang. Hire-mlp: Vision mlp via hierarchical rearrangement. arXiv preprint arXiv:2108.13341, 2021.

[32] Jean-Baptiste Cordonnier, Andreas Loukas, and Martin Jaggi. On the relationship between self-attention and convolutional layers. ICLR, 2020.

[33] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. arXiv preprint arXiv:2111.06377, 2021.

[34] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 9729–9738, 2020.

[35] Weihao Yu, Mi Luo, Pan Zhou, Chenyang Si, Yichen Zhou, Xinchao Wang, Jiashi Feng, and Shuicheng Yan. Metaformer is actually what you need for vision. arXiv preprint arXiv:2111.11418, 2021.

[36] Yaru Hao, Li Dong, Furu Wei, and Ke Xu. Self-attention attribution: Interpreting information interactions inside transformer. arXiv preprint arXiv:2004.11207, 2, 2020.

[37] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. arXiv preprint arXiv:1607.06450, 2016.

[38] Ross Wightman, Hugo Touvron, and Hervé Jégou. Resnet strikes back: An improved training procedure in timm. NeurIPS Workshop Track, 2021.

[39] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. International Conference on Learning Representations, 2022.
[40] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. Automatic differentiation in pytorch. 2017.

[41] Ross Wightman. Pytorch image models. https://github.com/rwightman/pytorch-image-models, 2019.

[42] Alex Rogozhnikov. Einops: Clear and reliable tensor manipulations with einstein-like notation. International Conference on Learning Representations, 2021.

[43] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. arXiv preprint arXiv:1710.09412, 2017.

[44] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junseuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In Proceedings of the IEEE/CVF international conference on computer vision, pages 6023–6032, 2019.

[45] Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? Advances in neural information processing systems, 32, 2019.

[46] Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, and Yi Yang. Random erasing data augmentation. In Proceedings of the AAAI conference on artificial intelligence, volume 34, pages 13001–13008, 2020.

[47] Frank Klinker. Exponential moving average versus moving exponential average. Mathematische Semesterberichte, 58(1):97–107, 2011.

[48] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q Weinberger. Deep networks with stochastic depth. In European conference on computer vision, pages 646–661. Springer, 2016.

[49] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation policies from data. arXiv preprint arXiv:1805.09501, 2018.

[50] Ekin D Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V Le. Randaugment: Practical automated data augmentation with a reduced search space. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 702–703, 2020.

[51] Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In 2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing, pages 722–729. IEEE, 2008.

[52] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101 – mining discriminative components with random forests. In European Conference on Computer Vision, 2014.

[53] Tesla NVIDIA. Nvidia tesla v100 gpu architecture, 2017.

[54] Yerlan Idelbayev. Proper ResNet implementation for CIFAR10/CIFAR100 in PyTorch. https://github.com/akamaster/pytorch_resnet_cifar10. Accessed: 2022-05-17.

[55] Ohad Shamir and Tong Zhang. Stochastic gradient descent for non-smooth optimization: Convergence results and optimal averaging schemes. In International conference on machine learning, pages 71–79. PMLR, 2013.