



Abstract

1 We present ResMLP, an architecture built entirely upon multi-layer perceptrons for
2 image classification. It is a simple residual network that alternates (i) a linear layer
3 in which image patches interact, independently and identically across channels, and
4 (ii) a two-layer feed-forward network in which channels interact independently per
5 patch. When trained with a modern training strategy using heavy data-augmentation
6 and optionally distillation, it attains surprisingly good accuracy/complexity trade-
7 offs on ImageNet. We also train ResMLP models in a self-supervised setup, to
8 further remove priors from employing a labelled dataset. Finally, by adapting our
9 model to machine translation we achieve surprisingly good results.

10 We will share our code based on the Timm library and pre-trained models.

11 1 Introduction

12 Recently, the transformer architecture [60], adapted from its original use in natural language pro-
13 cessing with only minor changes, has achieved performance competitive with the state of the art on
14 ImageNet-1k [50] when pre-trained with a sufficiently large amount of data [16]. Retrospectively,
15 this achievement is yet another step towards less priors: convolutional neural networks had removed
16 a lot of hand-made choices compared to hand-designed pre-CNN approaches, moving the paradigm
17 of hard-wired features to hand-designed architectural choices. Vision transformers avoid making
18 assumptions inherent to convolutional architectures and noticeably the translation invariance.

19 What these recent transformer-based works suggest is that longer training schedules, more parameters,
20 more data [16] and/or more regularization [56], are sufficient to recover the important priors for tasks
21 as complex as ImageNet classification. See also our discussion of related work in Section 4. This
22 concurs with recent studies [2, 15] that better disentangle the benefits from the architectures from
23 those of the training scheme.

24 In this paper, we push this trend further, and propose Residual Multi-Layer Perceptrons (ResMLP):
25 a purely multi-layer perceptron (MLP) based architecture for image classification. We outline our
26 architecture in Figure 1 and detail it further in Section 2. It is intended to be simple: it takes image
27 patches as input, projects them with a linear layer, and sequentially updates them in turn with two
28 residual operations: (i) a simple linear layer that provides interaction between the patches, which
29 is applied to all channels independently; and (ii) an MLP with a single hidden layer, which is
30 independently applied to all patches. At the end of the network, the patches are average pooled, and
31 fed to a linear classifier.

32 This architecture is strongly inspired by the vision transformers (ViT) [16], yet it is much simpler
33 in several ways: we do not use any form of attention, only linear layers along with the GELU
34 non-linearity [25]. Since our architecture is much more stable to train than transformers, we do not

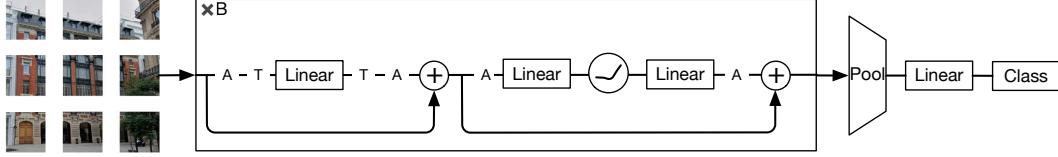


Figure 1: The ResMLP architecture: After linearly projecting the image patches, our network alternately processes them by (1) a communication layer between vectors implemented as a linear layer; (2) a two-layer residual perceptron. We denote by A the Affine element-wise transformation, and by T the transposition.

35 need batch-specific or cross-channel normalizations such as BatchNorm, GroupNorm or LayerNorm.
 36 Our training procedure mostly follows the one initially introduced for DeiT [56] and CaiT [57].

37 Due to its linear nature, the patch interactions in our model can be easily visualised and interpreted.
 38 While the interaction pattern learned in the first layer is very similar to a small convolutional filter,
 39 we observe more subtle interactions across patches in deeper layers. These include some form of
 40 axial filters, and long-range interactions early in the network.

41 In summary, in this paper, we show that

- 42 • despite their simplicity, Residual Multi-Layer Perceptrons reach surprisingly good accuracy/com-
 43 plexity trade-offs with ImageNet-1k training only¹, without requiring normalization based on batch
 44 or channel statistics;
- 45 • these models benefit significantly from distillation methods [56]; they are also compatible with
 46 modern self-supervised learning methods based on data augmentation, such as DINO [6];
- 47 • thank to its design where patch embeddings simply “communicate” through a linear layer, we can
 48 make observations on the spatial interaction that the network learns across layers;
- 49 • we adapt ResMLP to machine translation, and again obtain surprisingly good results.

50 2 Method

51 Our model, depicted in Figure 1, is inspired by the ViT model, from which we adopt the columnar
 52 structure with fixed-resolution feature maps. We proceed two drastic simplifications. We refer the
 53 reader to Dosovitskiy *et al.* [16] for more details about the ViT architecture.

54 **The overall ResMLP architecture.** Our model, denoted by ResMLP, takes a grid of $N \times N$ non-
 55 overlapping patches as input, where the patch size is typically equal to 16×16 . The patches are then
 56 independently passed through a linear layer to form a set of $N^2 d$ -dimensional embeddings.

57 The resulting set of N^2 embeddings are fed to a sequence of *Residual Multi-Layer Perceptron* layers
 58 to produce a set of $N^2 d$ -dimensional output embeddings. These output embeddings are then averaged
 59 as a d -dimension vector to represent the image, which is fed to a linear classifier to predict the label
 60 associated with the image. Training uses the cross-entropy loss.

61 **The Residual Multi-Perceptron Layer.** Our network is a sequence of layers that all have the same
 62 structure: a linear sublayer followed by a feedforward sublayer. Similar to the Transformer layer,
 63 each sublayer is paralleled with a skip-connection [23]. We do not apply Layer Normalization [1]
 64 because training is stable without it when using the following Affine transformation:

$$Aff_{\alpha, \beta}(x) = \text{Diag}(\alpha)x + \beta, \quad (1)$$

65 where α and β are learnable weight vectors. This operation simply rescales and shifts the input
 66 element-wise. Moreover, it has no cost at inference time, as it can be absorbed in the adjacent linear
 67 layer. Note, when writing $Aff(X)$ the operation is applied independently to each column of X .
 68 While similar to BatchNorm [30] and Layer Normalization [1], the Aff operator does not depend on
 69 any batch statistics. Therefore, it is closer to the recent LayerScale method [57], which improves the

¹Concurrent work by Tolstikhin *et al.* [55] brings complementary insights to ours: they achieve interesting performance with larger MLP models pre-trained on the larger public ImageNet-22k and even more data with the proprietary JFT-300M. In contrast, we focus on faster models trained on ImageNet-1k. Other concurrent related work includes that of Melas-Kyriazi [39] and the RepMLP [14] and gMLP [38] models.

70 optimization of deep transformers when initializing α to a small value. Note, LayerScale does not
71 have a bias term.

72 We apply this transformation twice for each residual block. As as a pre-normalization Aff replaces
73 the LayerNormalization, and avoids using channel-wise statistics. Here, we initialize $\alpha = 1$, and
74 $\beta = 0$. As a post-processing of the residual block, Aff implements LayerScale and therefore we
75 follow the same small value initialization for α as in [57] for the post-normalization.

76 Finally, we follow the same structure for the feedforward sublayer as in the Transformer; we only
77 replace the ReLU non-linearity by a GELU function [25].

78 Overall, our Multi-layer perceptron takes a set of $N^2 d$ -dimensional input features stacked in a
79 $d \times N^2$ matrix \mathbf{X} , and outputs a set of $N^2 d$ -dimension output features, stacked in a matrix \mathbf{Y} with
80 the following set of transformations:

$$\mathbf{Z} = \mathbf{X} + \text{Aff} \left((\mathbf{A} \text{Aff}(\mathbf{X})^\top)^\top \right), \quad (2)$$

$$\mathbf{Y} = \mathbf{Z} + \text{Aff}(\mathbf{C} \text{GELU}(\mathbf{B} \text{Aff}(\mathbf{Z}))), \quad (3)$$

81 where \mathbf{A} , \mathbf{B} and \mathbf{C} are the main learnable weight matrices of the layer. The dimensions of the
82 parameter matrix \mathbf{A} are $N^2 \times N^2$, i.e., this sublayer exchanges information across all the locations,
83 while the feedforward sublayer works per location. As a consequence, the intermediate activation
84 matrix \mathbf{Z} has the same dimensions as the matrices \mathbf{X} and \mathbf{Y} . Finally, the weight matrices \mathbf{B} and \mathbf{C}
85 have the same dimensions as in a Transformer layer, which are $4d \times d$ and $d \times 4d$, respectively.

86 The main difference compared to a Transformer layer is that we replace the self-attention by the
87 linear interaction defined in Eq. (2). While self-attention computes a convex combination of other
88 features with coefficients that are data dependent, the linear interaction layer in Eq. (2) computes
89 a general linear combination using learned coefficients that are not data dependent. As compared
90 to a convolutional layers which have local support and share weights across space, our linear
91 patch interaction layer offers a global support and does not share weights, moreover it is applied
92 independently across channels.

93 **Relationship to the Vision Transformer.** Our model can be regarded as a drastic simplification of
94 the ViT model by Dosovitskiy *et al.* [16]. We depart from this model as follows:

- 95 • We do not include any self-attention block. Instead we have a linear patch interaction layer without
96 any non-linearity.
- 97 • We do not have the extra “class” token that is typically used in these models to aggregate information
98 via attention. Instead, we simply use average pooling. We do, however, also consider a specific
99 aggregation layer as a variant, which we describe in the next paragraph.
- 100 • We do not include any form of positional embedding: the linear communication module between
101 patches implicitly takes into account the patch position.
- 102 • Instead of pre-LayerNormalization, we use a simple learnable affine transform, thus avoiding any
103 form of batch and channel-wise statistics.

104 **Class-MLP.** As an alternative to average pooling, we also experimented with an adaptation of the
105 class-attention introduced in CaiT [57]. In CaiT, this consists of two layers that have the same
106 structure as the transformer, but in which only the class token is updated based on the frozen patch
107 embeddings. We translate this method to our architecture, except that, after aggregating the patches
108 with a linear layer, we replace the attention-based interaction between the class and patch embeddings
109 by simple linear layers, still keeping the patch embeddings frozen. This increases the performance, at
110 the expense of adding some parameters and computational cost. We refer to this pooling variant as
111 “class-MLP”, since the purpose of these few layers is to replace average pooling.

112 3 Experiments

113 In this section, we present experimental results for our ResMLP architecture for image classification.
114 We also study the impact of the different components in a series of ablations. We consider three
115 training paradigms in our experiments:

Table 1: **Comparison between architectures on ImageNet classification.** We compare different architectures based on convolutional networks, Transformers and feedforward networks with comparable FLOPs and number of parameters. We report Top-1 accuracy on the validation set of ImageNet-1k with different measure of complexity: throughput, FLOPs, number of parameters and peak memory usage. All the models use 224×224 images as input. By default the Transformers and feedforward networks uses 14×14 patches of size 16×16 , see Table 3 for the detailed specification of our main models. The throughput is measured on a single V100-32GB GPU with batch size fixed to 32. For reference, we include the state of the art with ImageNet training only.

	Arch.	#params ($\times 10^6$)	throughput (im/s)	FLOPs ($\times 10^9$)	Peak Mem (MB)	Top-1 Acc.
<i>State of the art</i>	CaiT-M48↑448Υ [57] NfNet-F6 SAM [5]	356 438	5.4 16.0	329.6 377.3	5477.8 5519.3	86.5 86.5
<i>Convolutional networks</i>	EfficientNet-B3 [53]	12	661.8	1.8	1174.0	81.1
	EfficientNet-B4 [53]	19	349.4	4.2	1898.9	82.6
	EfficientNet-B5 [53]	30	169.1	9.9	2734.9	83.3
	RegNetY-4GF [47]	21	861.0	4.0	568.4	80.0
	RegNetY-8GF [47]	39	534.4	8.0	841.6	81.7
	RegNetY-16GF [47]	84	334.7	16.0	1329.6	82.9
<i>Transformer networks</i>	DeiT-S [56]	22	940.4	4.6	217.2	79.8
	DeiT-B [56]	86	292.3	17.5	573.7	81.8
	CaiT-XS24 [57]	27	447.6	5.4	245.5	81.8
<i>Feedforward networks</i>	ResMLP-S12	15	1415.1	3.0	179.5	76.6
	ResMLP-S24	30	715.4	6.0	235.3	79.4
	ResMLP-B24	116	231.3	23.0	663.0	81.0

- *Supervised learning:* We train ResMLP from labeled images with a softmax classifier and cross-entropy loss. This paradigm is the main focus of our work.
- *Self-supervised learning:* We train the ResMLP architecture without labels. We consider the DINO method of Caron *et al.* [6] that trains a network by distilling knowledge from previous instances of the same network, leading to a form of self-distillation without labels.
- *Knowledge distillation:* We employ the knowledge distillation procedure proposed by Touvron *et al.* [56] to guide the supervised training of ResMLP with a convnet.

123 3.1 Experimental setting

124 **Datasets.** We train our models on the ImageNet-1k dataset [50], that contains 1.2M images evenly
 125 spread over 1,000 object categories. In the absence of an available test set for this benchmark, we
 126 follow the standard practice in the community by reporting performance on the validation set. This
 127 is not ideal since the validation set was originally designed to select hyper-parameters. Comparing
 128 methods on this set may not be conclusive enough because an improvement in performance may not
 129 be caused by better modeling, but by a better selection of hyper-parameters. To mitigate this risk, we
 130 report additional results in transfer learning and on two alternative versions of ImageNet that have
 131 been built to have distinct validation and test sets, namely the ImageNet-real [3] and ImageNet-v2 [49]
 132 datasets. We also report a few data-points when training on ImageNet-21k. Our hyper-parameters are
 133 mostly adopted from Touvron *et al.* [56, 57].

134 **Hyper-parameter settings.** In the case of supervised learning, we train our network with the Lamb
 135 optimizer [63] with a learning rate of 5×10^{-3} and weight decay 0.2. We initialize the LayerScale
 136 parameters as a function of the depth by following CaiT [57]. The rest of the hyper-parameters follow
 137 the default setting used in DeiT [56]. For the knowledge distillation paradigm, we use the same
 138 RegNetY-16GF [48] as in DeiT with the same training schedule. The majority of our models take two
 139 days to train on eight V100-32GB GPUs.

140 3.2 Main Results

141 In this section, we compare our architecture to models with more conventional network architectures
 142 of comparable size and throughput on ImageNet.

143 **Comparison with Transformers and convnets in a supervised setting.** In Table 1, we compare
 144 ResMLP with different convolutional and Transformer architectures. For completeness, we report

Table 2: **Self-supervised learning** with DINO [6]. Classification accuracy on ImageNet-1k val. ResMLPs evaluated with linear and k -NN evaluation on ImageNet are comparable to convnets but inferior to ViT.

Models	ResNet-50	ViT-S/16	ViT-S/8	ViT-B/16	ResMLP-S12	ResMLP-S24
Params. ($\times 10^6$)	25	22	22	87	15	30
FLOPS ($\times 10^9$)	4.1	4.6	22.4	17.5	3.0	6.0
Linear	75.3	77.0	79.7	78.2	67.5	72.8
k -NN	67.5	74.5	78.3	76.1	62.6	69.4

145 the best-published numbers obtained with a model trained on ImageNet alone. As expected, in
 146 terms of the trade-off between accuracy, FLOPs, and throughput, ResMLP is not as efficient as
 147 convolutional networks or Transformers. However, their accuracy is encouraging: we compare them
 148 with architectures that have benefited from years of research and careful optimization towards these
 149 trade-offs. Overall, our results suggest that the structural constraints imposed by the layer design do
 150 not have a drastic influence on performance, especially when training models with enough data and
 151 recent advances in training and regularization.

152 **Self-supervised pre-training of ResMLP.** We explore the possibility of training ResMLP using
 153 DINO, a recent self-supervised learning approach [6]. We pre-train ResMLP-S12 models with this
 154 approach during 300 epochs. We report our results in Table 2. As expected given the supervised
 155 classification results, the accuracies obtained with ResMLP are less good than with ViT. Nevertheless,
 156 the performance is surprisingly high for a pure MLP architecture and competitive with Convnet in
 157 knn evaluation. We hope that these result will serve as a baseline for future work.

158 After self-supervised pre-training, we also fine-tune the network on ImageNet using ground truth
 159 labels. This pre-training substantially improves the accuracy, when comparing with the same model
 160 ResMLP-S24 solely trained with labels (top-1 acc. of 79.9% on ImageNet-val instead of 79.4% for
 161 ResMLP-S24, with the same total number of epochs). Results on ImageNet-v2 suggest that it reduces
 162 overfitting (68.6% on ImageNet-v2, vs 67.9% with supervised training only).

163 **Improving models with knowledge distillation.** We study our model when training following the
 164 knowledge distillation approach of Touvron *et al.* [56]. In their work, the authors show the impact of
 165 training a ViT model by distilling it from a RegNet. In this experiment, we explore if ResMLP also
 166 benefits from this procedure and summarize our results in Table 3 (Blocks “Baseline models” and
 167 “Training”). We observe that similar to DeiT models, ResMLP greatly benefits from distilling from a
 168 convnet. This result concurs with the observations made by d’Ascoli *et al.* [13], who used convnets
 169 to initialize feedforward networks. Even though our setting differs from theirs in scale, the problem
 170 of overfitting for feedforward networks is still present on ImageNet. The additional regularization
 171 obtained from the distillation is a possible explanation for this improvement.

172 **Visualisation.** Because they are linear, our patch interaction layers from Eq. (2) are easily inter-
 173 pretable. In Figure 2 we visualise the rows of the interaction matrices \mathbf{A} as $N \times N$ images, for our
 174 ResMLP-S24 model. The early layers show convolution-like patterns: the learned weights resemble
 175 shifted versions of each other and have local support. Interestingly, in many layers, the support also
 176 extends along both axes, most prominently seen in layer seven. The last seven layers of the network
 177 are different: they consist of a spike for the patch itself and a diffuse response across other patches
 178 with larger or smaller magnitude; see layer 20.

179 3.3 Visualization & analysis of the linear interaction between patches

180 **Measuring sparsity of the weights.** The visualizations described above suggest that the linear
 181 communication layers are sparse. We analyze this quantitatively in more detail in Figure 3. We
 182 measure the sparsity of the matrix \mathbf{A} , and compare it to the sparsity of \mathbf{B} and \mathbf{C} from the per-patch
 183 MLP. Since there are no exact zeros, we measure the rate of components whose absolute value is
 184 lower than 5% of the maximum value. Note, discarding the small values is analogous to the case
 185 where we normalize the matrix by its maximum and use a finite-precision representation of weights.
 186 For instance, with a 4-bits representation of weight, one would typically round to zero all weights
 187 whose absolute value is below 6.25% of the maximum value.

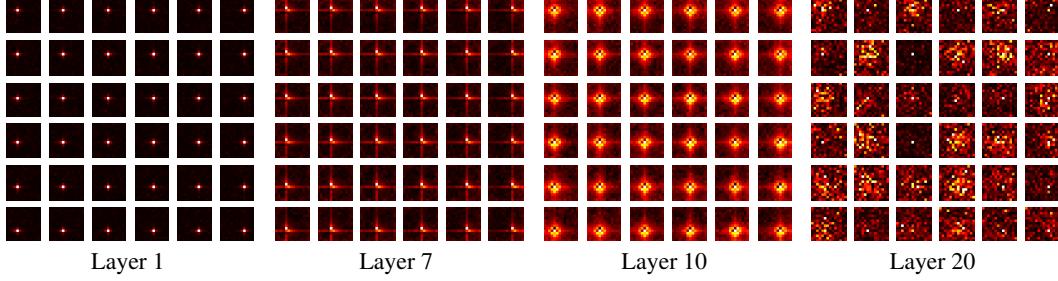


Figure 2: **Visualisation of the linear layers in ResMLP-S24.** For each layer we visualise the rows of the matrix \mathbf{A} as a set of 14×14 pixel images, for sake of space we only show the rows corresponding to the 6×6 central patches. We observe patterns in the linear layers that share similarities with convolutions. In appendix B we provide comparable visualizations for all layers of a ResMLP-S12 model.

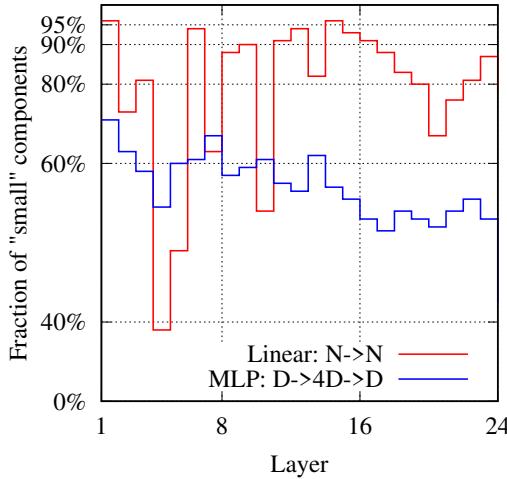


Figure 3: **Sparsity of linear interaction layers.** For each layer (linear and MLP), we show the rate of components whose absolute value is lower than 5% of the maximum. Linear interaction layers are sparser than the matrices involved in the per-patch MLP.

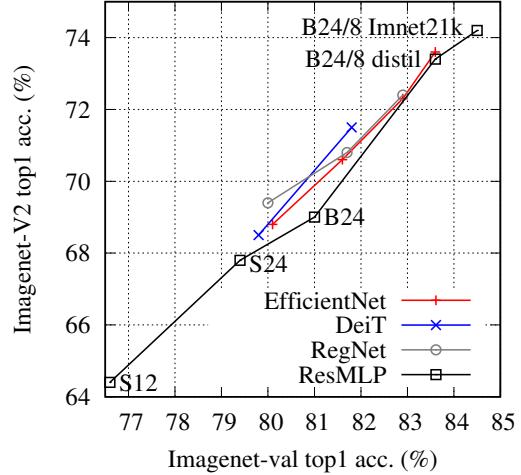


Figure 4: **Top-1 accuracy on ImageNet-V2 vs. ImageNet-val.** ResMLPs tend to overfit slightly more under identical training method. This is partially alleviated with by introducing more regularization (more data or distillation, see e.g., ResMLP-B24/8-distil).

188 The measurements in Figure 3 show that all three matrices are sparse, with the layers implementing
 189 the patch communication being significantly more so. This suggests that they may be compatible with
 190 parameter pruning, or better, with modern quantization techniques that induce sparsity at training
 191 time, such as Quant-Norm [20] and DiffQ [19]. The sparsity structure, in particular in earlier layers,
 192 see Figure. 2, hints that we could implement the patch interaction linear layer with a convolution. We
 193 provide some results for convolutional variants in our ablation study. Further research on network
 194 compression is beyond the scope of this paper, yet we believe it worth investigating in the future.

195 **Communication across patches** if we remove the linear interaction layer (linear → none), we
 196 obtain substantially lower accuracy (-20% top-1 acc.) for a “bag-of-patches” approach. We have tried
 197 several alternatives for the linear patch interaction layer, which are presented in Table 3 (block “patch
 198 communication”). Amongst them, using the same MLP structure as for patch processing (linear →
 199 MLP), which we analyze in more details in the supplementary material. The simpler choice of a
 200 single linear square layer led to a better accuracy/performance trade-off – considering that the MLP
 201 variant requires compute halfway between ResMLP-S12 and ResMLP-S24 – and requires fewer
 202 parameters than a residual MLP block.

203 The visualization in Figure 2 indicates that many linear interaction layers look like convolutions. In
 204 our ablation, we replaced the linear layer with different types of 3×3 convolutions. The depth-wise
 205 convolution does not implement interaction across channels – as our linear patch communication
 206 layer – and yields similar performance at a comparable number of parameters and FLOPs. While
 207 full 3×3 convolutions yield best results, they come with roughly double the number of parameters

Ablation	Model	Patch size	Params $\times 10^6$	FLOPs $\times 10^9$	Variant	top-1 acc. on ImageNet val	real [3]	v2 [49]	
Baseline models	ResMLP-S12	16	15.4	3.0	12 layers, working dimension 384	76.6	83.3	64.4	
	ResMLP-S24	16	30.0	6.0	24 layers, working dimension 384	79.4	85.3	67.9	
	ResMLP-B24	16	115.7	23.0	24 layers, working dimension 768	81.0	86.1	69.0	
Normalization	ResMLP-S12	16	15.4	3.0	$\text{Aff} \rightarrow \text{Layernorm}$		77.7	84.1	65.7
Pooling	ResMLP-S12	16	17.7	3.0	average pooling \rightarrow Class-MLP		77.5	84.0	66.1
Patch communication	ResMLP-S12	16	14.9	2.8	linear \rightarrow none	56.5	63.4	43.1	
	ResMLP-S12	16	18.6	4.3	linear \rightarrow MLP	77.3	84.0	65.7	
	ResMLP-S12	16	30.8	6.0	linear \rightarrow conv 3x3	77.3	84.4	65.7	
	ResMLP-S12	16	14.9	2.8	linear \rightarrow conv 3x3 depth-wise	76.3	83.4	64.6	
	ResMLP-S12	16	16.7	3.2	linear \rightarrow conv 3x3 depth-separable	77.0	84.0	65.5	
Patch size	ResMLP-S12/14	14	15.6	4.0	patch size 16x16 \rightarrow 14x14	76.9	83.7	65.0	
	ResMLP-S12/8	8	22.1	14.0	patch size 16x16 \rightarrow 8x8	79.1	85.2	67.2	
	ResMLP-B24/8	8	129.1	100.2	patch size 16x16 \rightarrow 8x8	81.0	85.7	68.6	
Training	ResMLP-S12	16	15.4	3.0	old-fashioned (90 epochs)	69.2	76.0	56.1	
	ResMLP-S12	16	15.4	3.0	pre-trained SSL (DINO)	76.5	83.6	64.5	
	ResMLP-S12	16	15.4	3.0	distillation	77.8	84.6	66.0	
	ResMLP-S24	16	30.0	6.0	pre-trained SSL (DINO)	79.9	85.9	68.6	
	ResMLP-S24	16	30.0	6.0	distillation	80.8	86.6	69.8	
	ResMLP-B24/8	8	129.1	100.2	distillation	83.6	88.4	73.4	
	ResMLP-B24/8	8	129.1	100.2	pre-trained ImageNet-21k (60 epochs)	84.4	88.9	74.2	

Table 3: **Ablation.** Our default configurations are presented in the three first rows. By default we train during 400 epochs. The “old-fashioned” is similar to what was employed for ResNet [23]: SGD, 90-epochs waterfall schedule, same augmentations up to variations due to library used.

and FLOPs. Interestingly, the depth-separable convolutions combine accuracy close to that of full 3×3 convolutions with a number of parameters and FLOPs comparable to our linear layer. This suggests that convolutions on low-resolution feature maps at all layers is an interesting alternative to the common pyramidal design of convnets, where early layers operate at higher resolution and smaller feature dimension.

3.4 Ablation studies

Table 3 reports the ablation study of our base network and a summary of our preliminary exploratory studies. We discuss the ablation below and give more detail about early experiments in Appendix A.

Control of overfitting. Since MLPs are subject to overfitting, we show in Fig. 4 a control experiment to probe for problems with generalization. We explicitly analyze the differential of performance between the ImageNet-val and the distinct ImageNet-V2 test set. The relative offsets between curves reflect to which extent models are overfitted to ImageNet-val w.r.t. hyper-parameter selection. The degree of overfitting of our MLP-based model is overall neutral or slightly higher to that of other transformer-based architectures or convnets with same training procedure.

Normalization & activation. Our network configuration does not contain any batch normalizations. Instead, we use the affine per-channel transform Aff . This is akin to Layer Normalization [1], typically used in transformers, except that we avoid to collect any sort of statistics, since we do no need it for convergence. In preliminary experiments with pre-norm and post-norm [24], we observed that both choices converged. Pre-normalization in conjunction with Batch Normalization could provide an accuracy gain in some cases, see Appendix A.

We choose to use a GELU [25] function. In Appendix A we also analyze the activation function: ReLU [22] also gives a good performance, but it was a bit more unstable in some settings. We did not manage to get good results with SiLU [25] and HardSwish [28].

Pooling. Replacing average pooling with Class-MLP, see Section 2, brings a significant gain for a negligible computational cost. We do not include it by default to keep our models more simple.

Patch size. Smaller patches significantly increase the performance, but also increase the number of flops (see Block “Patch size” in Table 3). Smaller patches benefit more to larger models, but only with an improved optimization scheme involving more regularization (distillation) or more data.

Training. Consider the Block “Training” in Table 3. ResMLP significantly benefits from modern training procedures such as those used in DeiT. For instance, the DeiT training procedure improves

Architecture	FLOPs	Res.	CIFAR ₁₀	CIFAR ₁₀₀	Flowers102	Cars	iNat ₁₈	iNat ₁₉
EfficientNet-B7 [53]	37.0B	600	98.9	91.7	98.8	94.7	—	—
ViT-B/16 [16]	55.5B	384	98.1	87.1	89.5	—	—	—
ViT-L/16 [16]	190.7B	384	97.9	86.4	89.7	—	—	—
Deit-B/16 [56]	17.5B	224	99.1	90.8	98.4	92.1	73.2	77.7
ResNet50 [58]	4.1B	224	—	—	96.2	90.0	68.4	73.7
Grafit/ResNet50 [58]	4.1B	224	—	—	97.6	92.7	68.5	74.6
ResMLP-S12	3.0B	224	98.1	87.0	97.4	84.6	60.2	71.0
ResMLP-S24	6.0B	224	98.7	89.5	97.9	89.5	64.3	72.5

Table 4: **Evaluation on transfer learning.** Classification accuracy (top-1) of models trained on ImageNet-1k for transfer to datasets covering different domains. The ResMLP architecture takes 224×224 images during training and transfer, while ViTs and EfficientNet-B7 work with higher resolutions, see “Res.” column.

238 the performance of ResMLP-S12 by 7.4% compared to the training employed for ResNet [23]².
 239 This is in line with recent work pointing out the importance of the training strategy over the model
 240 choice [2, 48]. Pre-training on more data and distillation also improve the performance of ResMLP,
 241 especially for the bigger models, *e.g.*, distillation improves the accuracy of ResMLP-B24/8 by 2.6%.

242 **Other analysis.** In our early exploration, we evaluated several alternative design choices. As in
 243 transformers, we could use positional embeddings mixed with the input patches. In our experiments
 244 we did not see any benefit from using these features, see Appendix A. This observation suggests that
 245 our linear patch interaction layer provides sufficient spatial communication, and referencing absolute
 246 positions obviates the need for any form of positional encoding.

247 3.5 Transfer learning

248 We evaluate the quality of features obtained from a ResMLP architecture when transferring them to
 249 other domains. The goal is to assess if the features generated from a feedforward network are more
 250 prone to overfitting on the training data distribution. We adopt the typical setting where we pre-train
 251 a model on ImageNet-1k and fine-tune it on the training set associated with a specific domain. We
 252 report the performance with different architectures on various image benchmarks in Table 4, namely
 253 CIFAR-10 and CIFAR-100 [34], Flowers-102 [42], Stanford Cars [33] and iNaturalist [27]. We refer
 254 the reader to the corresponding references for a more detailed description of the datasets. We observe
 255 that the performance of our ResMLP is competitive with the existing architectures, showing that
 256 pretraining feedforward models with enough data and regularization via data augmentation greatly
 257 reduces their tendency to overfit on the original distribution. Interestingly, this regularization also
 258 prevents them from overfitting on the training set of smaller dataset during the fine-tuning stage.

259 3.6 Machine translation

260 We also evaluate the ResMLP transpose-mechanism to replace the self-attention in the encoder and
 261 decoder of a neural machine translation system. We train models on the WMT 2014 English-German
 262 and English-French tasks, following the setup from Ott *et al.* [45]. We consider models of dimension
 263 512, with a hidden MLP size of 2048, and with 6 or 12 layers. Note that the current state of the art
 264 employs much larger models: our 6 layers model is more comparable to the base transformer model
 265 from Vaswani *et al.* [60], which serves as a baseline, along with pre-transformer architectures such as
 266 Recurrent and convolutional neural networks. We use Adagrad with learning rate 0.2, 32k steps of
 267 linear warmup, label smoothing 0.1, dropout rate 0.15 for en-de and 0.1 for en-fr. We initialize the
 268 LayerScale parameter to 0.2. We generate translations with the beam search algorithm, with a beam
 269 of size 4. As shown in Table 5, the results are at least on par with other architectures:

Table 5: **Machine translation** on WMT 2014 translation tasks. We report tokenized BLEU on *newstest2014*.

Models	GNMT [61]	ConvS2S [21]	Transf. (base) [60]	ResMLP-6	ResMLP-12
EN-DE	24.6	25.2	27.3	26.4	26.8
EN-FR	39.9	40.5	38.1	40.3	40.6

²Interestingly, if trained with this “old-fashion” setting, ResMLP-S12 outperforms AlexNet [35] by a margin.

270 **4 Related work**

271 We review the research on applying Fully Connected Network (FCN) for computer vision problems
272 as well as other architectures that shares common modules with our model.

273 **Fully-connected network for images.** Many studies have shown that FCNs are competitive with
274 convnets for the tasks of digit recognition [11, 51], keyword spotting [7] and handwritting recogni-
275 tion [4]. Several works [37, 40, 59] have questioned if FCNs are also competitive on natural image
276 datasets, such as CIFAR-10 [34]. More recently, d’Ascoli *et al.* [13] have shown that a FCN initialized
277 with the weights of a pretrained convnet achieves performance that are superior than the original
278 convnet. Neyshabur [41] further extend this line of work by achieving competitive performance by
279 training an FCN from scratch but with a regularizer that constrains the models to be close to a convnet.
280 These studies have been conducted on small scale datasets with the purpose of studying the impact of
281 architectures on generalization in terms of sample complexity [18] and energy landscape [31]. In
282 our work, we show that, in the larger scale setting of ImageNet, FCNs can attain surprising accuracy
283 without any constraint or initialization inspired by convnets.

284 Finally, the application of FCN networks in computer vision have also emerged in the study of
285 the properties of networks with infinite width [43], or for inverse scattering problems [32]. More
286 interestingly, the Tensorizing Network [44] is an approximation of very large FCN that shares
287 similarity with our model, in that they intend to remove prior by approximating even more general
288 tensor operations, *i.e.*, not arbitrarily marginalized along some pre-defined sharing dimensions.
289 However, their method is designed to compress the MLP layers of a standard convnets.

290 **Other architectures with similar components.** Our FCN architecture shares several components
291 with other architectures, such as convnets [35, 36] or transformers [60]. A fully connected layer is
292 equivalent to a convolution layer with a 1×1 receptive field, and several work have explored convnet
293 architectures with small receptive fields. For instance, the VGG model [52] uses 3×3 convolutions,
294 and later, other architectures such as the ResNext [62] or the Xception [10] mix 1×1 and 3×3
295 convolutions. In contrast to convnets, in our model interaction between patches is obtained via a
296 linear layer that is shared across channels, and that relies on absolute rather than relative positions.

297 More recently, transformers have emerged as a promising architecture for computer vision [9, 17,
298 46, 56, 66]. In particular, our architecture takes inspiration from the structure used in the Vision
299 Transformer (ViT) [17], and as consequence, shares many components. Our model takes a set
300 of non-overlapping patches as input and passes them through a series of MLP layers that share
301 the same structure as ViT, replacing the self-attention layer with a linear patch interaction layer.
302 Both layers have a global field-of-view, unlike convolutional layers. Whereas in self-attention the
303 weights to aggregate information from other patches are data dependent through queries and keys,
304 in ResMLP the weights are not data dependent and only based on absolute positions of patches. In
305 our implementation we follow the improvements of DeiT [56] to train vision transformers, use the
306 skip-connections from ResNets [23] with pre-normalization of the layers [8, 24].

307 Finally, our work questions the importance of self-attention in existing architectures. Similar ob-
308 servations have been made in natural language processing. Notably, Synthesizer [54] shows that
309 dot-product self-attention can be replaced by a feedforward network, with competitive performance
310 on sentence representation benchmarks. As opposed to our work, Synthesizer does use data dependent
311 weights, but in contrast to transformers the weights are determined from the queries only.

312 **5 Conclusion**

313 In this paper we have shown that a simple residual architecture, whose residual blocks consist of a
314 one-hidden layer feed-forward network and a linear patch interaction layer, achieves an unexpectedly
315 high performance on ImageNet classification benchmarks, provided that we adopt a modern training
316 strategy such as those recently introduced for transformer-based architectures. Thanks to their simple
317 structure, with linear layers as the main mean of communication between patches, we can visualize
318 the filters learned by this simple MLP. While some of the layers are similar to convolutional filters,
319 we also observe sparse long-range interactions as early as the second layer of the network. We hope
320 that our model free of spatial priors will contribute to further understanding of what networks with
321 less priors learn, and potentially guide the design choices of future networks without the pyramidal
322 design prior adopted by most convolutional neural networks.

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481 **Checklist**

- 482 1. For all authors...
- 483 (a) Do the main claims made in the abstract and introduction accurately reflect the paper's
484 contributions and scope? **[Yes]**
- 485 (b) Did you describe the limitations of your work? **[Yes]**
- 486 (c) Did you discuss any potential negative societal impacts of your work? **[No]** We only
487 use MLPs for image classification. There is already other system much more powerful
488 therefore the impact is negligible
- 489 (d) Have you read the ethics review guidelines and ensured that your paper conforms to
490 them? **[Yes]**
- 491 2. If you are including theoretical results...
- 492 (a) Did you state the full set of assumptions of all theoretical results? **[N/A]**
- 493 (b) Did you include complete proofs of all theoretical results? **[N/A]**
- 494 3. If you ran experiments...
- 495 (a) Did you include the code, data, and instructions needed to reproduce the main exper-
496 imental results (either in the supplemental material or as a URL)? **[Yes]** We provide
497 code in appendix
- 498 (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they
499 were chosen)? **[Yes]**
- 500 (c) Did you report error bars (e.g., with respect to the random seed after running experi-
501 ments multiple times)? **[No]** Because it's too expensive in computational resources. But
502 for some experiments we run multiple times and we have ~ 0.1 as standard deviation
- 503 (d) Did you include the total amount of compute and the type of resources used (e.g., type
504 of GPUs, internal cluster, or cloud provider)? **[Yes]** The majority of our experiments
505 take 2 days on 8 GPUs V100-32GB
- 506 4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
- 507 (a) If your work uses existing assets, did you cite the creators? **[Yes]**
- 508 (b) Did you mention the license of the assets? **[No]** But license can be found with the
509 references we mention
- 510 (c) Did you include any new assets either in the supplemental material or as a URL? **[No]**
- 511 (d) Did you discuss whether and how consent was obtained from people whose data you're
512 using/curating? **[No]** We only use datasets that are widely used in computer vision
513 such as ImageNet or CIFAR
- 514 (e) Did you discuss whether the data you are using/curating contains personally identifiable
515 information or offensive content? **[No]** We only use datasets that are widely used in
516 computer vision such as ImageNet or CIFAR
- 517 5. If you used crowdsourcing or conducted research with human subjects...
- 518 (a) Did you include the full text of instructions given to participants and screenshots, if
519 applicable? **[N/A]**
- 520 (b) Did you describe any potential participant risks, with links to Institutional Review
521 Board (IRB) approvals, if applicable? **[N/A]**
- 522 (c) Did you include the estimated hourly wage paid to participants and the total amount
523 spent on participant compensation? **[N/A]**