Lightweight neural architectures by example - car model classification using GhostNet

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Broader concept

1. Training different mobile architectures on an open car dataset and performance comparison in terms of:
    - accuracy
    - model size
    - inference efficiency
2. Preparing custom dataset and finetuning the best model to reflect real distribution
3. Creating a mobile application that will recognize car model in a picture taken by the user

This work's focus

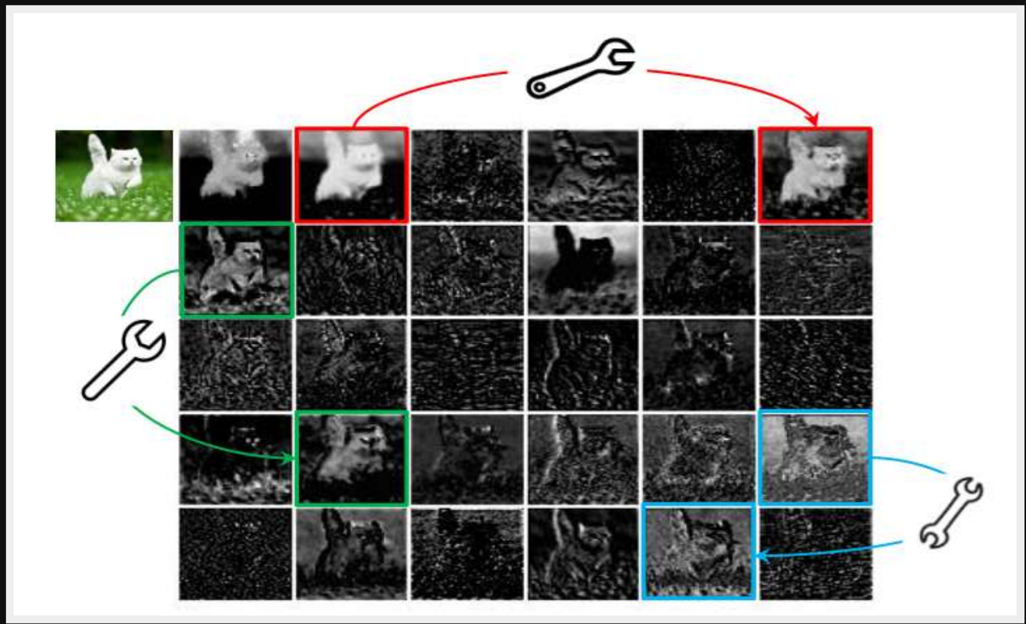
Applying different training techniques on GhostNet architecture to get the best accuracy on Stanford Cars Dataset.

Stanford Cars Dataset

- 16,185 images
- 50/50 stratified train/test split
- 196 classes (make, model, production year)
- bounding boxes
- differenet image sizes
- RGB (with some grayscale exceptions)

GhostNet

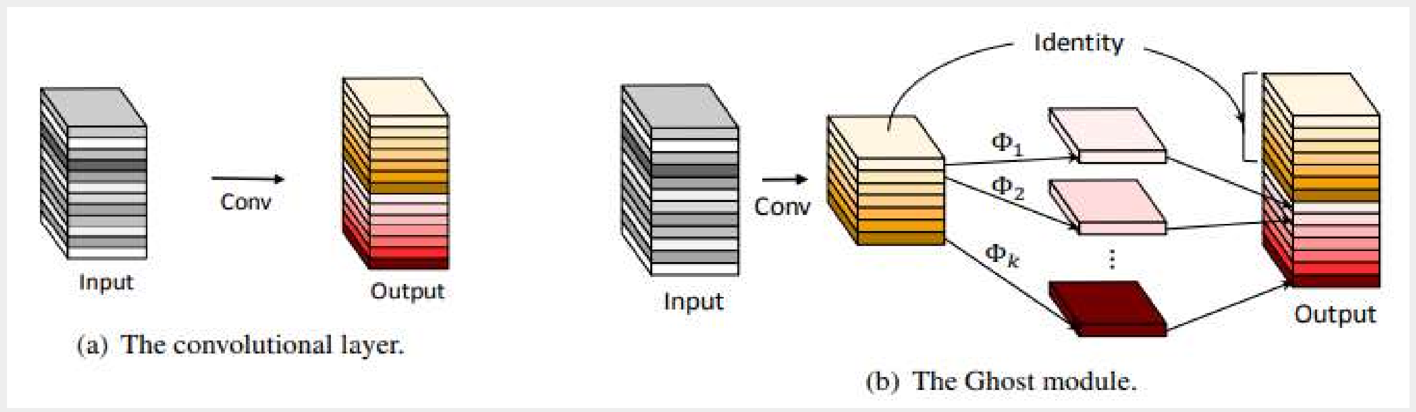
Main assumption: successful neural network designs use a lot of convolutional filters to create feature maps of which many are similar to each other. Let’s try to obtain those redundant feature maps in a more cost-efficient way.



GhostNet - GhostModule

GhostModule splits standard many-filter convolution into two parts, which are concatenated at the end:

1. also standard convolution, but with less filters to create a set of base feature maps
2. some cheap linear operations, that create redundant feature maps from base feature maps



(a) The convolutional layer.

(b) The Ghost module.

GhostModule in PyTorch

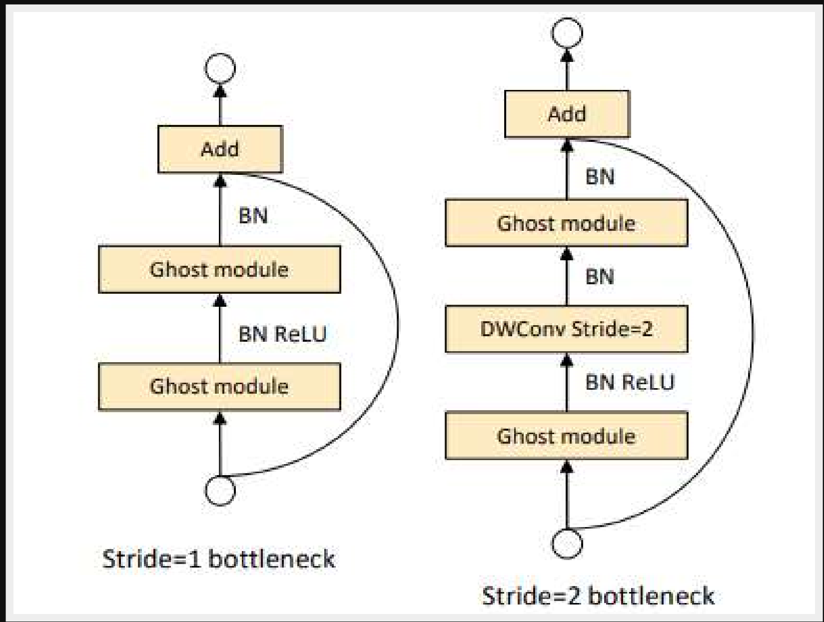
```
class GhostModule(nn.Module):
    def __init__(
        self, inp, oup,
        kernel_size=1, ratio=2, dw_size=3, stride=1,
        relu=True
    ):
        super().__init__()
        self.oup = oup
        init_channels = math.ceil(oup / ratio)
        new_channels = init_channels*(ratio-1)

        self.primary_conv = nn.Sequential(
            nn.Conv2d(
                inp, init_channels, kernel_size, stride,
                kernel_size//2, bias=False
            ),
            nn.BatchNorm2d(init_channels),
            nn.ReLU(inplace=True) if relu else nn.Sequential(),
        )

        self.cheap_operation = nn.Sequential(
            nn.Conv2d(init_channels, new_channels, dw_size, 1,
            dw_size//2, groups=init_channels, bias=False
        ),
            nn.BatchNorm2d(new_channels),
            nn.ReLU(inplace=True) if relu else nn.Sequential(),
        )
    def forward(self, input):
        output_1 = self.primary_conv(input)
        output_2 = self.cheap_operation(output_1)
        output = torch.cat([output_1, output_2], dim=1)
        return output[:, :self.oup, :, :]
```

GhostBottleneck

Two GhostModules = GhostBottleneck

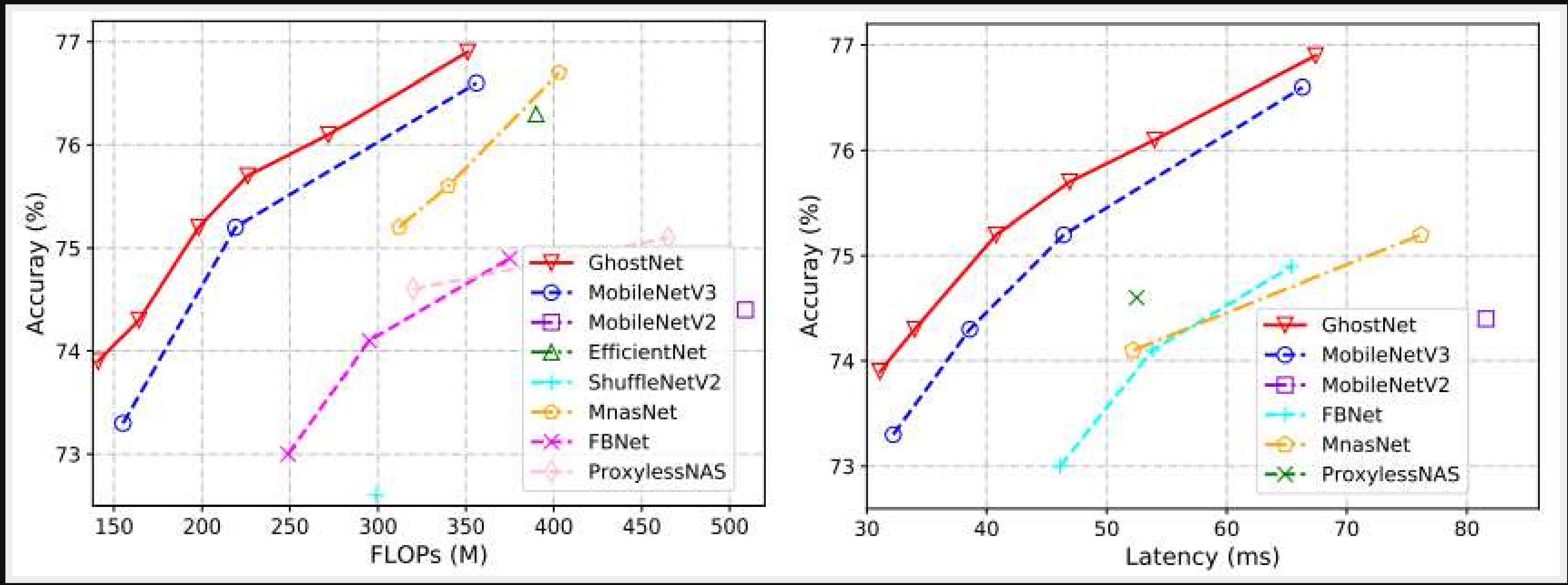


GhostNet setup

Input	Operator	#exp	#out	SE	Stride
224 x 224 x 3	Conv2d 3x3	-	16	-	2
112 x 112 x 16	G-bneck	16	16	-	1
112 x 112 x 16	G-bneck	48	24	-	2
56 x 56 x 24	G-bneck	72	24	-	1
56 x 56 x 24	G-bneck	72	40	1	2
28 x 28 x 40	G-bneck	120	40	1	1
28 x 28 x 40	G-bneck	240	80	-	2
14 x 14 x 80	G-bneck	200	80	-	1
14 x 14 x 80	G-bneck	184	80	-	1
14 x 14 x 80	G-bneck	184	80	-	1
14 x 14 x 80	G-bneck	480	112	1	1
14 x 14 x 112	G-bneck	672	112	1	1
14 x 14 x 112	G-bneck	672	160	1	2
7 x 7 x 160	G-bneck	960	160	-	1
7 x 7 x 160	G-bneck	960	160	1	1
7 x 7 x 160	G-bneck	960	160	-	1
7 x 7 x 160	G-bneck	960	160	1	1
7 x 7 x 160	Conv2d 1x1	-	960	-	1
7 x 7 x 960	AvgPool 7x7	-	-	-	-
1 x 1 x 960	Conv2d 1x1	-	1280	-	1
1 x 1 x 1280	FC	-	1000	-	-

GhostNet on ImageNet

- 73.98 % top-1 accuracy
- 4.1 M parameters
- 0.142 GFLOPS for processing 224x224 RGB



Experimentation setup

- **environment**: Python 3 + virtual env or Colab
- **framework**: PyTorch
- **training**: `pytorch-lightning==0.9`
- **configuration**: external YAML file
- **logs and tracking**: Neptune.ai
- **runtime**: either local Windows/Linux with GPU and CUDA or remote Google Colab (also simultaneous sessions)
- **code storage**: GitHub

Training assumptions

- training and validation subsets (no test)
- no pre-training
- image size: 227x227 (RGB or grayscale)
- batch size: 64
- Adam or AdamW when using weight decay
- early stopping after 15 epochs if no decrease in validation loss

Techniques for training

- different loss functions
- pixel value normalization
- various image augmentations
- grayscale conversion
- utilization of bounding boxes
- L2 regularization using weight decay
- dropout rate changing in the classifier module
- last layer size changing
- learning rate scheduling

Experiments results summary (1/2)

	experiment description	train_acc	valid_acc
C-1	Baseline (Cross Entropy Loss)	92.49%	8.15%
C-2	Loss function change (Label Smoothing Cross Entropy)	98.89%	9.12%
C-3	Added RGB normalization	99.45%	11.96%
C-4	Augmentations: horizontal flip, affine, erasing	99.76%	51.92%
C-5	Augmentations: horizontal flip, erasing, color jitter	98.12%	38.08%
C-6	Augmentations: horiz. flip, affine, erasing, color jitter	93.68%	38.68%
C-7	Augmentations: horizontal flip, affine, color jitter	99.73%	54.28%
C-8	Grayscale: with normalization, no augmentations	99.49%	6.58%
C-9	Grayscale: with normalization, no augmentations	97.13%	8.68%
C-10	Training set cropping with bounding boxes	7.58%	3.91%
C-11	Training set cropping + background erasing	4.36%	3.07%
C-12	Grayscale: normalization, best RGB augmentations	99.67%	50.51%
C-13	L2 regularization with AdamW: weight decay = 0.1	99.44%	63.39%
C-14	L2 regularization with AdamW: weight decay = 0.2	98.84%	68.50%
C-15	L2 regularization with AdamW: weight decay = 0.3	95.83%	61.84%
C-16	L2 regularization with AdamW: weight decay = 0.4	95.95%	65.14%
C-17	L2 regularization with AdamW: weight decay = 0.5	90.38%	59.95%
C-18	Dropout rate tests: dropout = 0.1	99.11%	66.90%
C-19	Dropout rate tests: dropout = 0.3	98.62%	67.81%
C-20	Dropout rate tests: dropout = 0.4	96.52%	64.88%
C-21	Dropout rate tests: dropout = 0.5	96.28%	66.75%
C-22	Last layer size tests: out channels = 320	97.13%	68.93%
C-23	Last layer size tests: out channels = 640	96.13%	63.13%
C-24	Last layer size tests: out channels = 960	98.23%	64.96%
C-25	Last layer size tests: out channels = 1600	98.99%	63.11%
C-26	Automatic LR scheduling: take #1	99.82%	74.60%
C-27	Automatic LR scheduling: take #2	99.78%	76.20%
C-28	Automatic LR scheduling: take #3	99.83%	75.14%

Experiments results summary (2/2)

	experiment description	train_acc	valid_acc
C-29	Automatic LR scheduling: take #4	99.78%	74.82%
C-30	Controlled LR scheduling: milestones = [28, 48, 68, 88]	80.66%	57.82%
C-31	Controlled LR scheduling: milestones = [36, 56, 76, 96]	95.03%	64.93%
C-32	Controlled LR scheduling: milestones = [44, 64, 84, 104]	98.68%	68.79%
C-33	Controlled LR scheduling: milestones = [52, 72, 92, 112]	99.60%	71.59%
C-36	Weight decay adjustment: weight decay = 0.5	98.84%	79.40%
C-37	Weight decay adjustment: weight decay = 0.3	99.57%	74.44%
C-38	Weight decay adjustment: weight decay = 0.4	99.37%	78.82%
C-39	Weight decay adjustment: weight decay = 0.6	98.67%	82.55%
C-40	Weight decay adjustment: weight decay = 0.7	99.24%	75.12%
C-41	Dropout rate verification: dropout = 0.3	98.49%	82.08%
C-42	Dropout rate verification: dropout = 0.4	95.34%	79.57%
C-43	Dropout rate verification: dropout = 0.5	96.08%	77.87%
C-44	Dropout rate verification: dropout = 0.25	98.79%	82.45%
C-45	Additional augmentations test: resized crop	97.56%	78.73%
C-46	Additional augmentations test: rotation	97.03%	78.25%
C-47	Additional augmentations test: perspective	97.42%	80.22%
C-48	Additional augmentations test: erasing	93.68%	80.56%
C-50	**LR scheduler adjustment: milestones = [67, 82, 95, 107]**	**98.94%**	**83.79%**
C-51	LR scheduler adjustment: milestones = [63, 78, 91, 103]	98.86%	82.54%
C-53	LR scheduler adjustment: milestones = [66, 81, 94, 106]	98.96%	83.02%
C-55	LR scheduler adjustment: milestones = [68, 83, 96, 108]	98.78%	83.72%
C-56	LR scheduler adjustment: milestones = [64, 79, 92, 104]	98.99%	82.79%
C-58	Last layer size sanity check: out channels = 1280	99.44%	78.83%
C-63	LR annealing test: LR geometric sequence	99.80%	70.51%
C-64	LR annealing test: exponentiation base = 0.955	98.49%	60.70%
C-65	LR annealing test: exponentiation base = 0.975	99.66%	73.07%
C-66	LR annealing test: exponentiation base = 0.98	98.72%	70.46%

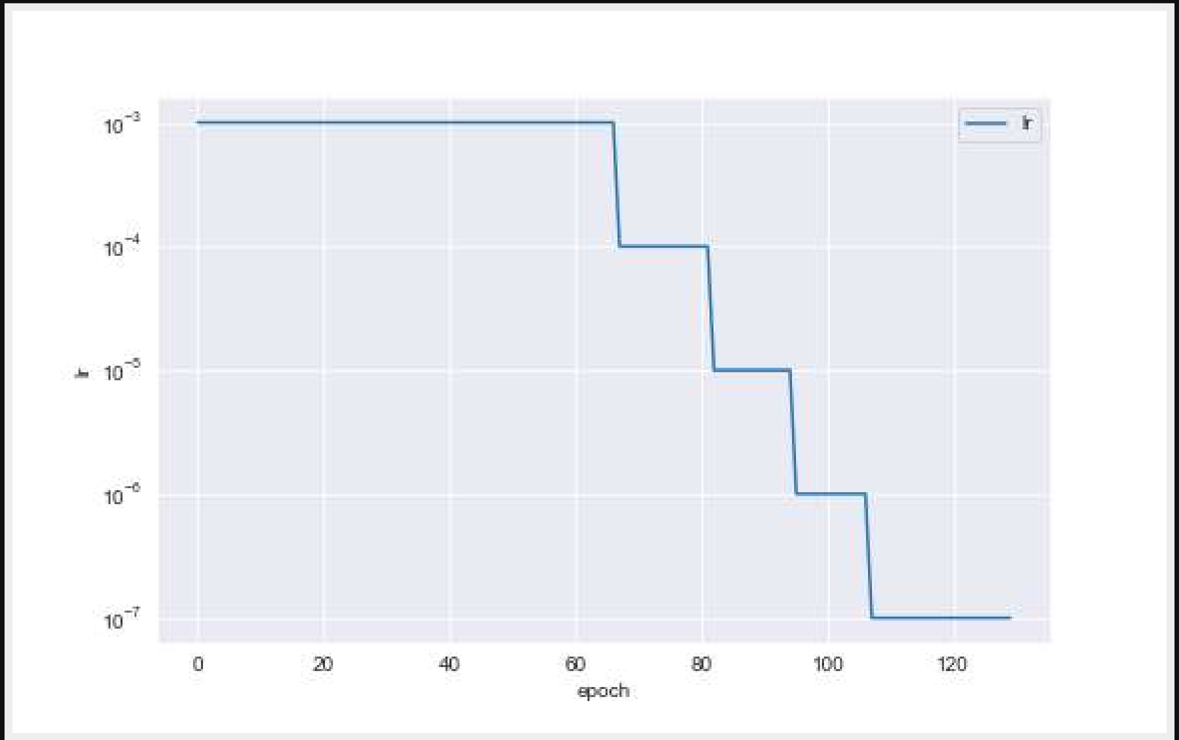
Best Model settings

Parameter	Value
runtime	colab
architecture	GhostNet
num_params	3041412
img_size	[227, 227]
grayscale	0
normalize	1
norm_params_rgb	{'mean': [0.4707, 0.4602, 0.455], 'std': [0.2594, 0.2585, 0.2635]}
norm_params_gray	None
crop_to_bboxes	0
erase_background	0
augment_images	1
image_augmentations	{'RandomHorizontalFlip': {'p': 0.5}, 'RandomAffine': {'degrees': 25, 'translate': [0.1, 0.1], 'scale': [0.9, 1.1], 'shear': 8}, 'ColorJitter': {'brightness': 0.2, 'contrast': 0.2, 'saturation': 0.2, 'hue': 0.1}}
augment_tensors	0
tensor_augmentations	None
batch_size	64
max_num_epochs	200
dropout	0.2
out_channels	320
loss_function	LabelSmoothingCrossEntropy
loss_params	None
optimizer	AdamW
learning_rate	0.001
weight_decay	0.6
all_optimizer_params	{'lr': 0.001, 'weight_decay': 0.6}
lr_scheduler	MultiStepLR
lr_scheduler_params	{'gamma': 0.1, 'milestones': [67, 82, 95, 107]}

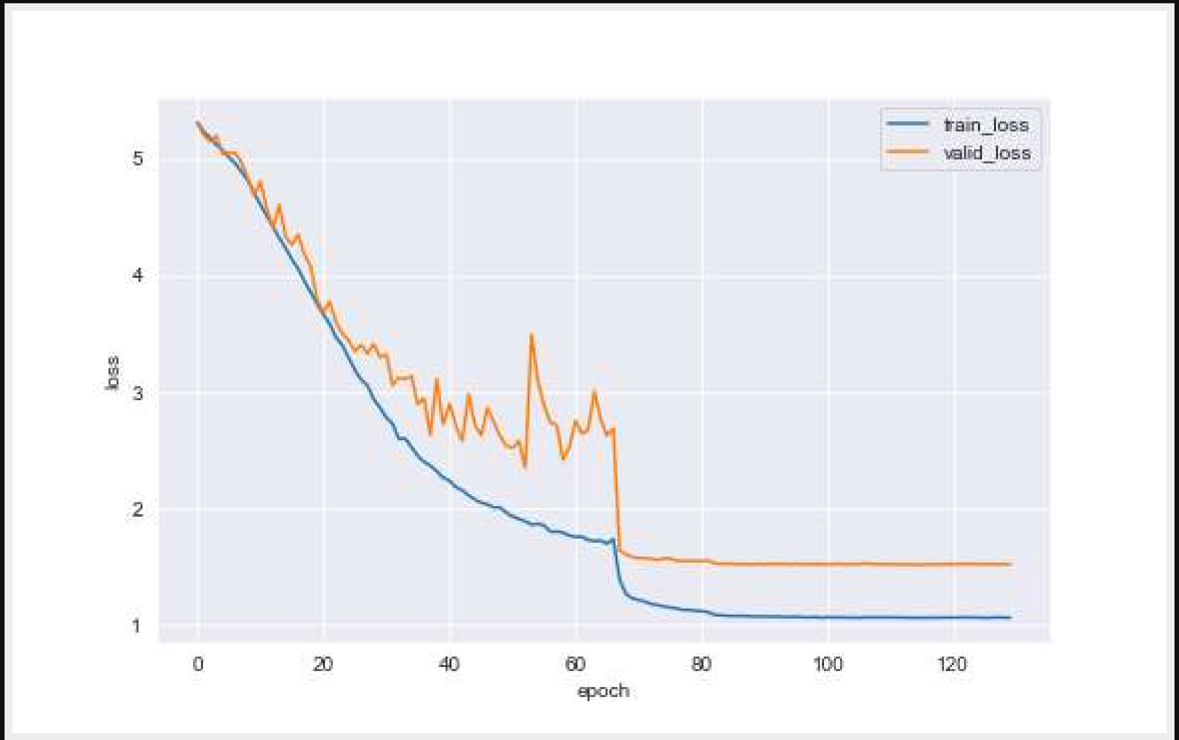
Best model results

Metric	Value
Min. training loss	1.064
Min. validation loss	1.521
Max. training accuracy	98.93%
Max. validation accuracy	83.79%

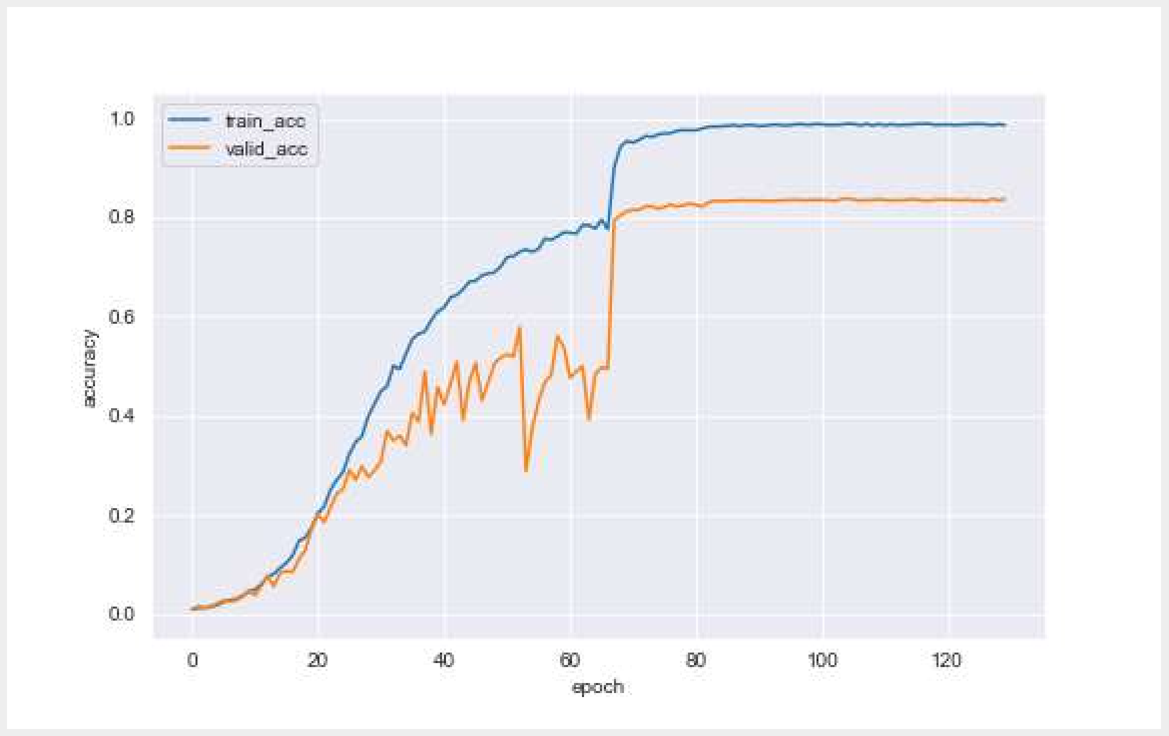
Best model - learning rate



Best model - loss (LSCE)



Best model - top-1 accuracy



Thank You!

github.com/pchaberski/cars