Solution for Stanford-cars classification

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I. SUMMARY

This solution for challenge https://www.aiforsea.com/computer-vision.
In this challenge, I have to build a cars classifier using the Stanford cars dataset, which contains 196 classes (including make and model). This is a normal image classification, but it is not easy to achieve high accuracy in the short time of challenge.
Key idea:

- Build strong single model on training set:
  - Different CNN architectures
  - Different image input sizes
  - Train with different augmentation schedules
  - 12 crops for predicting
- Ensemble different models

My final accuracy is 0.9462, higher accuracy than state-of-the-art stanford cars 2018 [1] (0.945) and nearly state-of-the-art image classification on stanford cars 2019 (0.947) [2]

II. DATASET

- 196 classes
- Trainset: 8144 images
- Testset: 8041 images

Some images in training set:

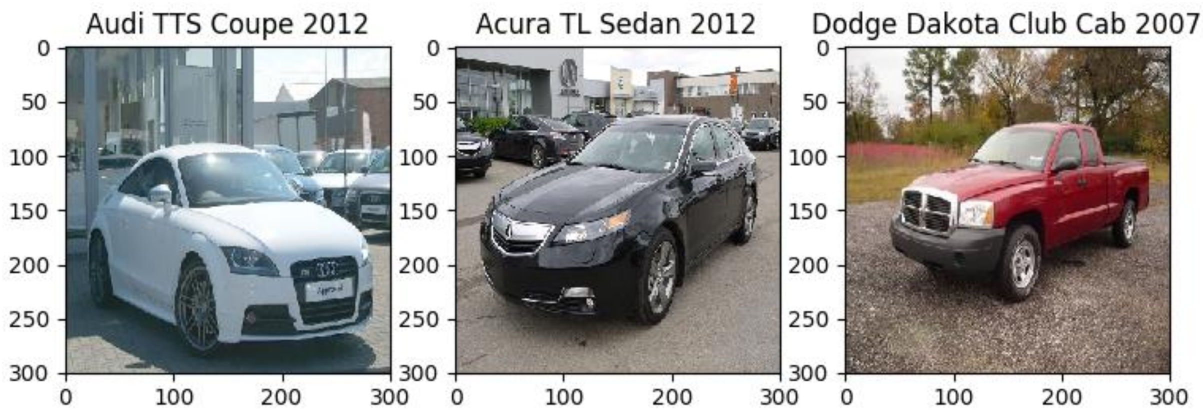


Figure 1: samples in training set

Distribution of training set:

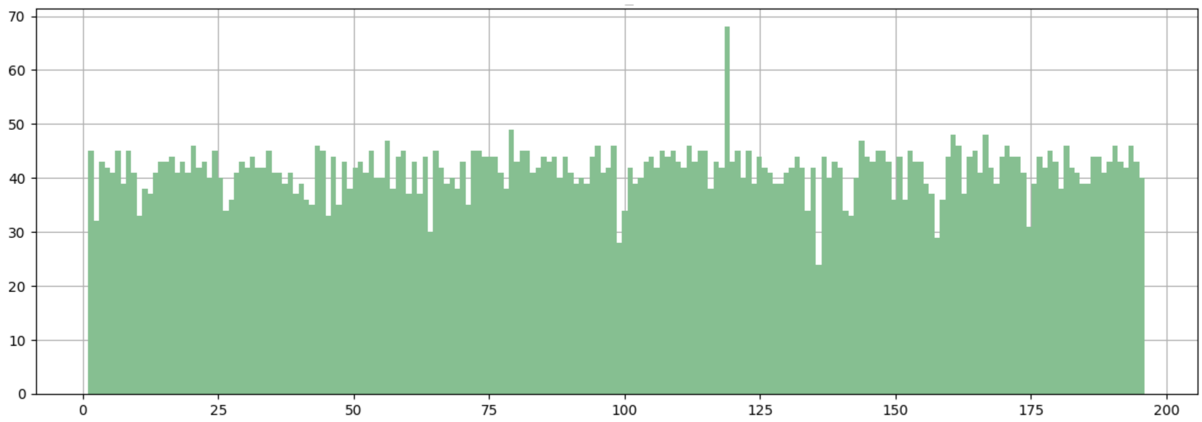


Figure 2: Distribution of training set

Min: 24 images/class, max: 68 images/class, mean: 41 images/class, so this dataset is quite balanced.

III. TRAINING DETAILS

- Different CNN architectures, using pre-trained weights on imagenet dataset, with transfer learning to train the model. All layers will be fine tuned and the last fully connected layer will be replaced entirely. 7 main models in this solution: EfficientNetB1, EfficientNetB2, EfficientNetB3, ResNeXt101, DenseNet201, ResNet152V2, NASNetLarge.
- Different image input sizes: 224x224x3, 331x331x3, 240x240x3, 260x260x3, 300x300x3, 320x320x3, 384x384x3, 416x416x3
- Train with heavy augmentation:
    - random crops, horizontal flip, rotate, shear, AddToHueAndSaturation, AddMultiply, GaussianBlur, ContrastNormalization, sharpen, emboss
    - Random eraser [3]
    - Mixup [4]
- Using cyclical learning rates for training models [5]
- Cross-validation 5 folds
- Add dropout 0.5 at the last dense layer before output layer

IV. EVALUATE MODELS

To enhance the result, I applied 12 crops for validation and test prediction. Accuracy of single model is ensemble of 12 crops and 5 folds. For example with input shape of network is 224x224x3:

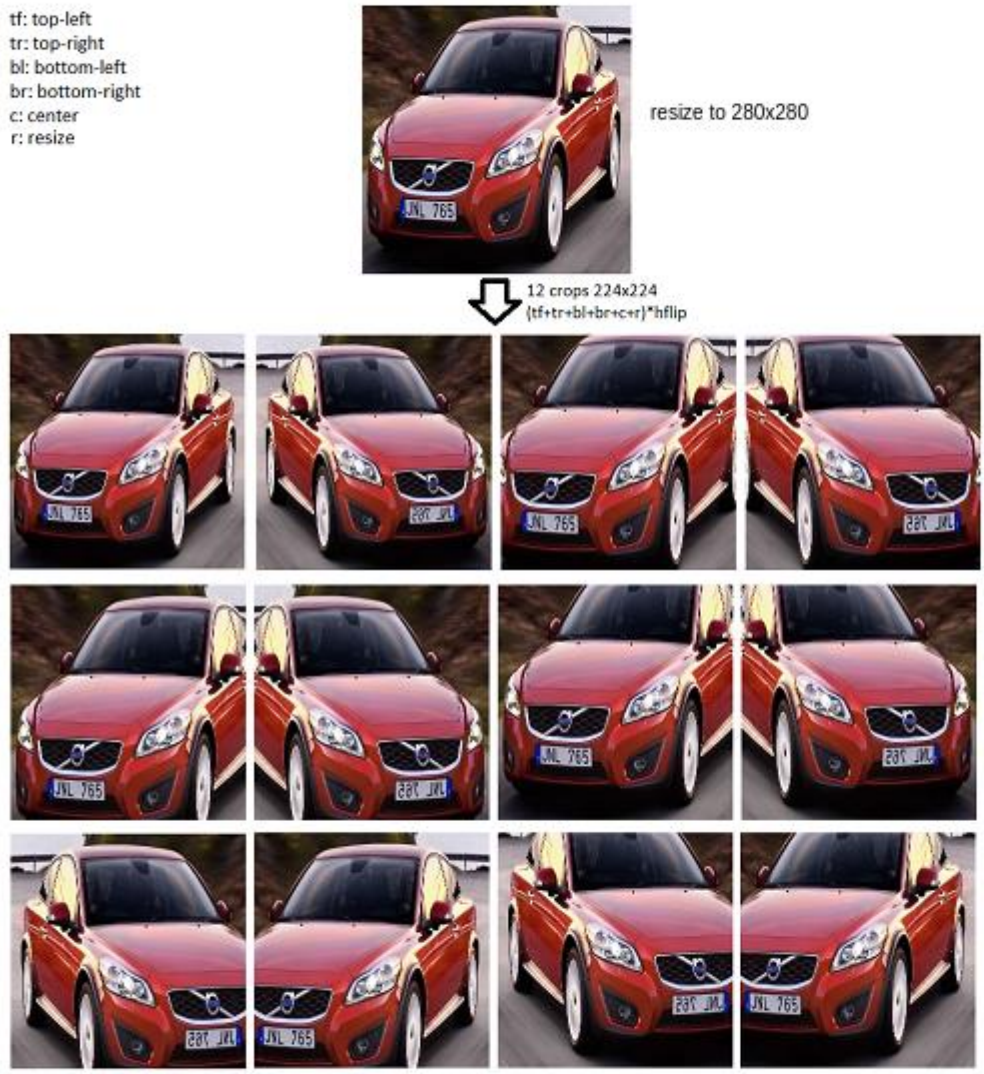


Figure 3: 12 crops for predicting

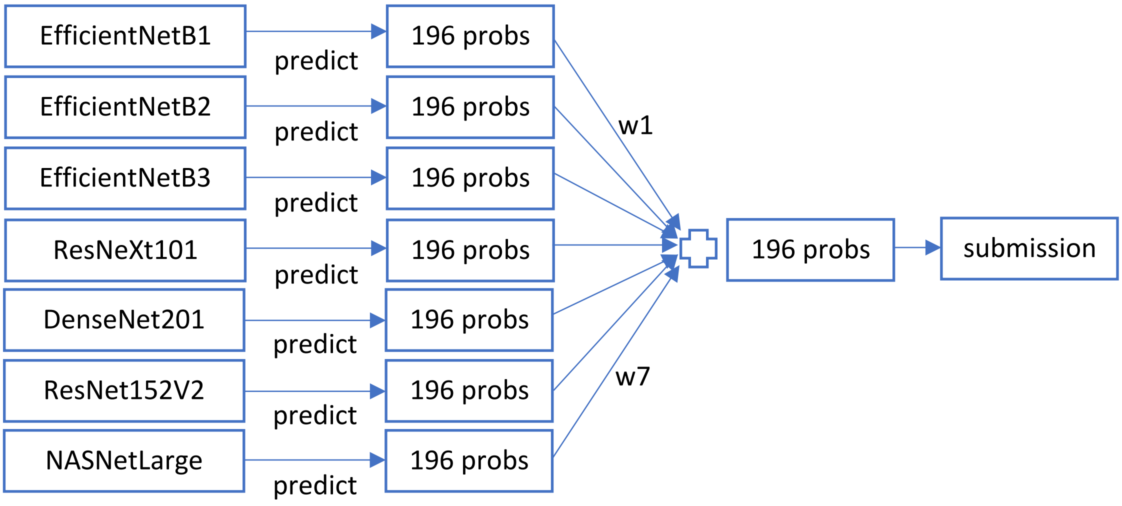
Accuracy and size of 13 single models:

Models	Pretrain accuracy (imagenet)	Accuracy (stanford car)	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4	Size
ResNeXt101	0.787	Val-acc	0.8999	0.9196	0.9184	0.9214	0.9300	179 MB
		Val-acc 12 crops	0.9239	0.9349	0.9269	0.9269	0.9337	
		Test-acc 12 crops	0.9226	0.9304	0.9271	0.9236	0.9342	
		Test-acc ensemble 5 folds	**0.9413**					
DenseNet201	0.773	Val-acc	0.9073	0.9196	0.9104	0.9208	0.9232	83 MB
		Val-acc 12 crops	0.9177	0.9263	0.9171	0.9294	0.9330	
		Test-acc 12 crops	0.9224	0.9295	0.9169	0.9246	0.9245	
		Test-acc ensemble 5 folds	0.9396					
ResNeXt50	0.777	Val-acc	0.9073	0.9147	0.9190	0.9122	0.9128	102MB
		Val-acc 12 crops	0.9165	0.9319	0.9263	0.9257	0.9275	
		Test-acc 12 crops	0.9195	0.9289	0.9231	0.9248	0.9254	
		Test-acc ensemble 5 folds	0.9391					
NASNetLarge	0.825	Val-acc	0.8999	0.9085	0.9091	0.9104	0.9214	358 MB
		Val-acc 12 crops	0.9134	0.9202	0.9171	0.9257	0.9281	
		Test-acc 12 crops	0.9241	0.9195	0.9197	0.9235	0.9275	
		Test-acc ensemble 5 folds	0.9389					
EfficientNetB3	0.811	Val-acc	0.9067	0.9085	0.9141	0.9153	0.9214	51 MB
		Val-acc 12 crops	0.9110	0.9122	0.9171	0.9282	0.9312	
		Test-acc 12 crops	0.9239	0.9203	0.9209	0.9209	0.9277	
		Test-acc ensemble 5 folds	0.9352					
InceptionV3	0.779	Val-acc	0.9055	0.9091	0.9098	0.9184	0.9177	97MB
		Val-acc 12 crops	0.9159	0.9190	0.9196	0.9349	0.9287	
		Test-acc 12 crops	0.9218	0.9210	0.9132	0.9266	0.9197	
		Test-acc ensemble 5 folds	0.9347					
ResNet152V2	0.780	Val-acc	0.8858	0.9079	0.8920	0.8821	0.9036	243 MB
		Val-acc 12 crops	0.9128	0.9257	0.9208	0.9141	0.9244	
		Test-acc 12 crops	0.9179	0.9219	0.9151	0.9108	0.9205	
		Test-acc ensemble 5 folds	0.9342					
EfficientNetB2	0.798	Val-acc	0.9036	0.9018	0.9153	0.9012	0.9097	38 MB
		Val-acc 12 crops	0.9177	0.9147	0.9184	0.9153	0.9177	
		Test-acc 12 crops	0.9204	0.9217	0.9202	0.9126	0.9149	
		Test-acc ensemble 5 folds	0.9325					
Xception	0.790	Val-acc	0.8877	0.8956	0.9018	0.8969	0.9097	101 MB
		Val-acc 12 crops	0.9085	0.9110	0.9110	0.9159	0.9232	
		Test-acc 12 crops	0.9136	0.9185	0.9154	0.9110	0.9171	
		Test-acc ensemble 5 folds	0.9312					
MobileNetV2	0.713	Val-acc	0.8815	0.9006	0.8938	0.9024	0.9048	**15 MB**
		Val-acc 12 crops	0.8938	0.9122	0.9079	0.9184	0.9214	
		Test-acc 12 crops	0.9024	0.9141	0.9023	0.9102	0.9134	
		Test-acc ensemble 5 folds	0.9294					
InceptionResNetV2	0.803	Val-acc	0.8877	0.8926	0.8760	0.8883	0.9115	225 MB
		Val-acc 12 crops	0.9036	0.9110	0.8969	0.9177	0.9251	
		Test-acc 12 crops	0.9121	0.9126	0.8985	0.9113	0.9194	
		Test-acc ensemble 5 folds	0.9280					
EfficientNetB1	0.788	Val-acc	0.8956	0.9030	0.9036	0.9024	0.9023	33 MB
		Val-acc 12 crops	0.9006	0.9116	0.9141	0.9141	0.9165	
		Test-acc 12 crops	0.9105	0.9151	0.9118	0.9146	0.9152	
		Test-acc ensemble 5 folds	0.9276					
EfficientNetB0	0.763	Val-acc	0.8834	0.8987	0.8920	0.8735	0.8907	23 MB
		Val-acc 12 crops	0.8907	0.9122	0.9030	0.8932	0.9165	
		Test-acc 12 crops	0.9023	0.9070	0.9040	0.8935	0.9054	
		Test-acc ensemble 5 folds	0.9182					

Figure 4: Accuracy and size of 13 models

V. ENSEMBLE

To boost accuracy, I ensemble 7 main model with suitable ratio



My result:

Cars 196 Submission Site

Your account is **dungnb1333@gmail.com.** If this is incorrect, please contact jkrause@cs.stanford.edu.

Please provide your name

Name: Dung Nguyen Ba

Submit results using the form below. **You must wait 24 hours between submissions.**

The current time is 2019/06/15 11:28:10

last upload: Ensemble.txt. size: 35806 bytes. uploaded at 2019/06/13 10:17:43 Pacific time.

Accuracy: 94.6150976246736%

Result file: here

VI. GUIDELINE

Step by step how to run my source code: https://github.com/dungnb1333/stanford-cars-classification

- Environments
  - Ubuntu 16.04 LTS
  - Cuda 10.0, cuDNN v7.5.0
  - Python 3.5, Keras 2.2.4, Tensorflow 1.13.1, Efficientnet
  - Quick install dependencies:
  - $ pip install --upgrade -r requirement.txt

- Step1: Prepare dataset

Download dataset

$ bash quick_download.sh

Cross-validation 5 folds

$ python3 prepare.py

- Step2: Traing 7 main models:

```
$ python3 train.py --network EfficientNetB1 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network EfficientNetB2 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network EfficientNetB3 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network ResNeXt101 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network DenseNet201 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network ResNet152V2 --gpu 0 --epochs 200 --multiprocessing False
$ python3 train.py --network NASNetLarge --gpu 0 --epochs 200 --multiprocessing False
```

Note: my repository contains the checkpoint and logs of 13 models trained on Stanford-cars dataset. If you don't want to train models, you just download them and put into folder checkpoints

Link checkpoints:

https://www.dropbox.com/sh/jv7dbd5ksj2exun/AAATZFgaxe7rMEjv10PG1BYha?dl=0

Link training logs:

https://github.com/dungnb1333/stanford-cars-classification/tree/master/logs

- Step3: Predict 7 models on stanford cars test set:

```
$ python3 predict.py --network EfficientNetB1 --gpu 0
$ python3 predict.py --network EfficientNetB2 --gpu 0
$ python3 predict.py --network EfficientNetB3 --gpu 0
$ python3 predict.py --network ResNeXt101 --gpu 0
$ python3 predict.py --network DenseNet201 --gpu 0
$ python3 predict.py --network ResNet152V2 --gpu 0
$ python3 predict.py --network NASNetLarge --gpu 0
```

Output: 7 network.txt in folder submission and 7 raw output network.npy in folder data

If you don't want to predict, just download raw output and put them to folder data

Link: https://www.dropbox.com/sh/gem7sd15oc974w8/AACeMvoChN3GnFfRCeSBEoHAa?dl=0

- Step4: Ensemble:

$ python3 ensemble.py

Output: submission file Ensemble.txt in folder submission.

Now you can summit it at stanford-cars evaluation server

http://imagenet.stanford.edu/internal/car196/submission/submission.php

- Demo on single image:

You should run on single model to save time, otherwise you can run on multiple models and ensemble results to achieve higher accuracy

$ python3 demo.py --network network --gpu gpu_id --image_path path --imshow True/False

For example:
$ python3 demo.py --network ResNeXt101 --gpu 0 --image_path images/samples/02381.jpg --imshow True

Figure 5: demo on image

VII. IMPORTANT NOTE FOR PRIVATE TEST SET

I don't like this challenge because it's too unclear: not ranking, not provide private set (just images), not provide format of private test submission … If candidate's solution runs very well on stanford cars set test (even higher accuracy than state-of-the-art) but your evaluators can't run ours models on a private test dataset by reasons like format of private test set ... That's really bad because we spent a lot of time for this challenge.

If you run my solution on private test set, please

- replace images in folder **datasets/cars_test** by your private test set, format of private test images must be "%05d.jpg"
- provide bounding box of car in private test images by replace **datasets/devkit/cars_test_annos.mat**
- replace line 6 (self.conf.TEST_NUMS = 8041) in file **config.py** by number of private test images
- Then run python3 prepare.py >> step3 >> step4 in GUIDELINE

If you don't have bounding box annotation **cars_test_annos.mat** for private test set, just replace images in folder **datasets/crop_test** by your private test set, format of private test images must be "%05d.jpg", then replace line 6 in file **config.py** >> step3 >> step4 in GUIDELINE.

REFERENCES

[1] State-of-the-art stanford cars dataset 2018 https://paperswithcode.com/sota/fine-grained-image-classification-on-stanford
[2] State-of-the-art stanford cars dataset 2019 https://paperswithcode.com/sota/image-classification-on-stanford-cars
[3] Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, Yi Yang: Random Erasing Data Augmentation
[4] Hongyi Zhang, Moustapha Cisse, Yann N. Dauphin, David Lopez-Paz: mixup - Beyond Empirical Risk Minimization
[5] Leslie N. Smith: Cyclical Learning Rates for Training Neural Networks