







Kaggle 경진대회문제

식물의 여러 사진을 보고 어떠한 질병에 인지 확인하는 문제

예측값이 여러개의 항목으로 이루어져있으며, 예측값의 확률을 계산하는 다중분류문제이다.



EDA

Data Explorer

823.79 MB

- images
 - sample_submission.csv
 - test.csv
 - train.csv

test.head()

image_id				
0	Test_0			
1	Test_1			
2	Test_2			
3	Test_3			
4	Test_4			

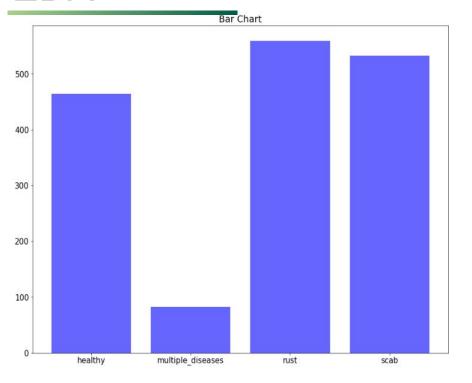
train.head()

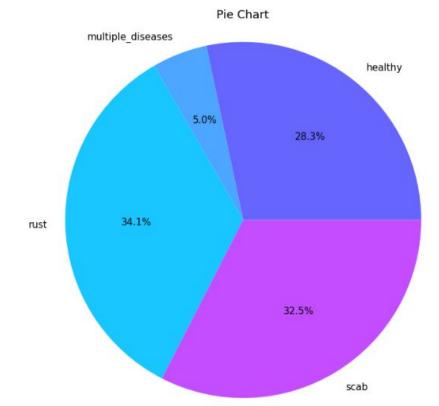
	image_id	healthy	multiple_diseases	rust	scab
379	Train_379	0	0	0	1
1556	Train_1556	1	0	0	0
448	Train_448	1	0	0	0
1202	Train_1202	0	0	0	1
1541	Train_1541	1	0	0	0

submission.head()

	image_id	healthy	multiple_diseases	rust	scab
0	Test_0	0.25	0.25	0.25	0.25
1	Test_1	0.25	0.25	0.25	0.25
2	Test_2	0.25	0.25	0.25	0.25
3	Test_3	0.25	0.25	0.25	0.25
4	Test_4	0.25	0.25	0.25	0.25

EDA





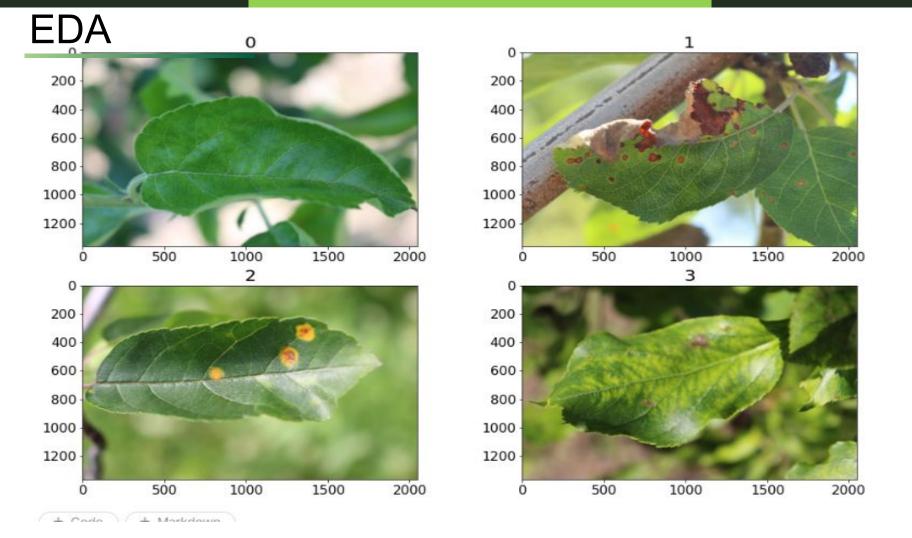
healthy : 건강함

multiple_diseases : 여러 질병

rust : 녹병균

scab : 붉은 곰팡이병

예측값이 4개로 하는 다중분류





전 처 리

Albumentation library

- Horizontal
- Vertical
- RandomBright
- Affine
- ShiftscaleRotate
- Normalize
- Blur, Sharpen, Emboss,

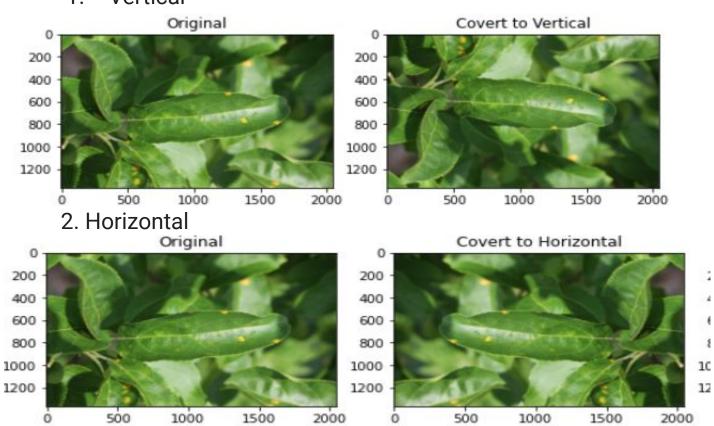
```
import albumentations as A
from albumentations.pytorch import ToTensorV2
```

```
transform_train = A.Compose([
   #A. Resize(450, 850).
   A.Resize(320, 512),
   A.RandomBrightnessContrast(brightness_limit=0.2, # 밝기 대비 조절
                             contrast_limit=0.2, p=0.3),
   A. VerticalFlip(p=0.2),
   A. HorizontalFlip(p=0.5).
   A.ShiftScaleBotate(
       shift_limit=0.1.
       scale_limit=0.2.
       rotate_limit=30, p = 0.3),
   A.OneOf([A.Emboss(p=1), # 양각화, 날카로움, 불러 효과
            A.Sharpen(p=1).
            A.Blur(p=1)], p=0.3),
   A.PiecewiseAffine(p=0.3), # 어파인 변환
   A.Normalize(), # 정규화 변환
   ToTensorV2() # 則서로 변환
```

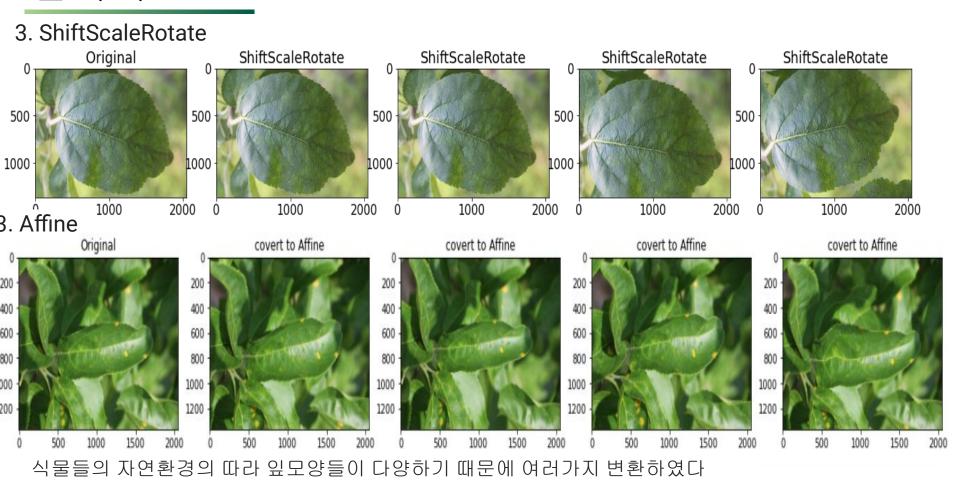
```
transform_test = A.Compose([
#A.Resize(450,850),
A.Resize(320, 512),
A.Normalize(),
ToTensorV2()
])
```

전처리

1. Vertical

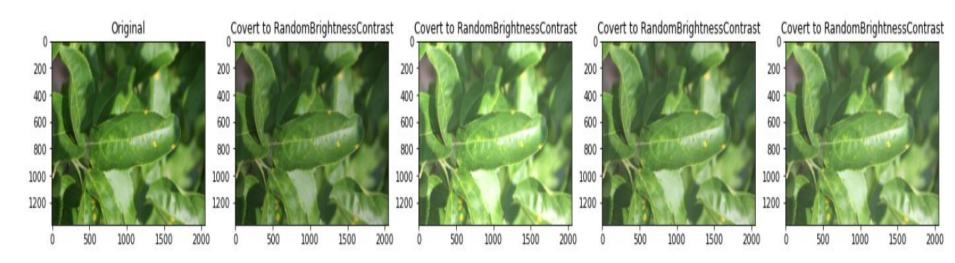


전처리



전처리

5. RandomBrightneessConstrast



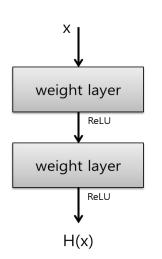
식물들은 대부분 야외에서 자라기때문에 랜덤한 빛의 형태가 필요하다고 생각



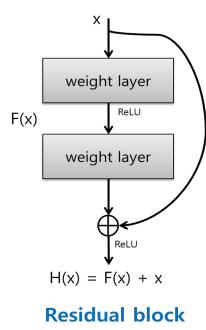
- 1. Resnet50
- 2. EfficientNetB0
- 3. EfficientNetB4
- 3. EfficientNetB7

Model 4종류 선정

Resnet50



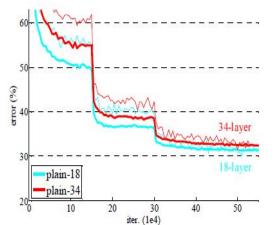
기존 방식

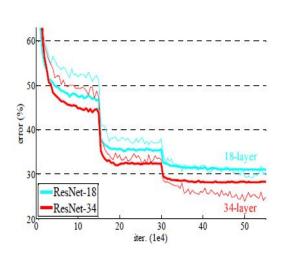


다들 아시겠지만...

$$F(x) + x$$

VGG-19 구조로 하며 기존모델은 layer를 깊게하면 오히려 정확도가 낮았지만 shortcut을 사용하여 x 학습난이도를 낮추고 layer를 깊게하여 성능을 높임





- 빠른 성능으로 ImageNet SOTA 달성
- 적은 parameter로 transfer 또한 잘 됨

EfficientNetB0~B7

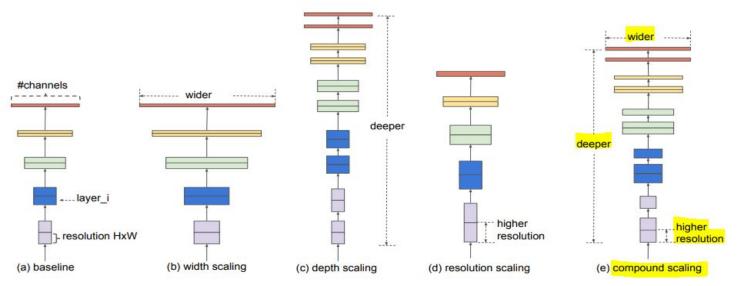
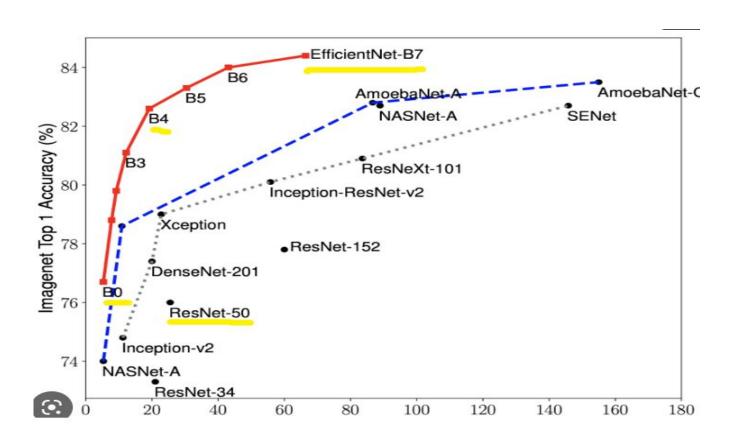


Figure 2. Model Scaling. (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

기존 모델에선 (width, depth, resolution) 임의로 한가지 요소를 scale

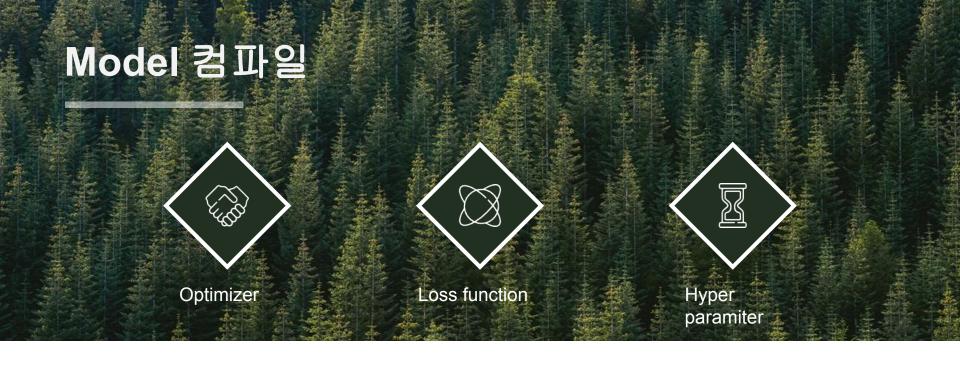
EfficientNet은 세가지 요소를 균일하게 scale

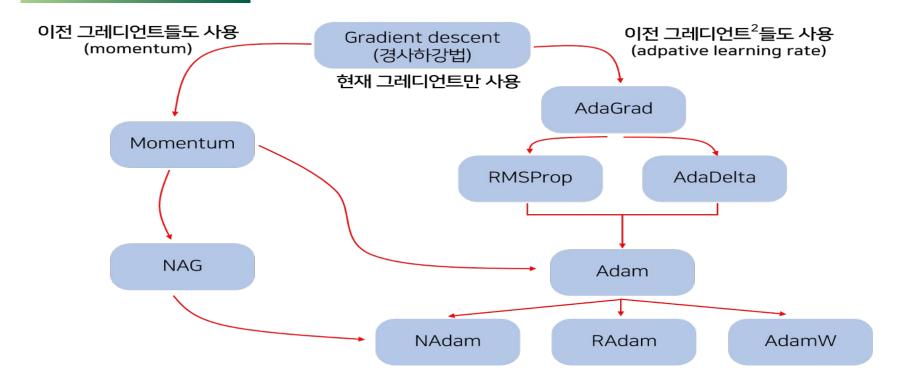


Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNe
EfficientNet-B0	77.1%	93.3%	5.3M	1x	0.39B	1x
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	79.1%	94.4%	7.8M	1x	0.70B	1x
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	80.1%	94.9%	9.2M	1x	1.0B	1x
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	81.6%	95.7%	12M	1x	1.8B	1x
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	82.9%	96.4%	19M	1x	4.2B	1x
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	83.6%	96.7%	30M	1x	9.9B	1x
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	84.0%	96.8%	43M	1x	19B	1x
EfficientNet-B7	84.3%	97.0%	66M	1x	37B	1x
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

We omit ensemble and multi-crop models (Hu et al., 2018), or models pretrained on 3.5B Instagram images (Mahajan et al., 2018).







옵티마이저는 대부분 Adam을 사용하지만, 발전된 모델인 AdamW와 성능을 비교하였음.

손실함수로 교차엔트로피 선정

$$\mathcal{L} = \sum_{i=1}^n ext{CrossEntropy}(\hat{y}_i, y_i) \ ext{where } \hat{y}_i \in \mathbb{R}^3, y_i \in \{0, 1\}^3 ext{ and } |y_i| = 1.$$

 $ext{CrossEntropy}(\hat{y}i,y_i) = -y_i imes \log \hat{y}_i$

train.head()

	image_id	healthy	multiple_diseases	rust	scab
379	Train_379	0	0	0	1
1556	Train_1556	1	0	0	0
448	Train_448	1	0	0	0
1202	Train_1202	0	0	0	1
1541	Train_1541	1	0	0	0

Label이 one-hot 벡터로 구성되어있고, 클래스가 4개, CrossEntopy가 적합하다고 판단.

하이퍼파라미터

Epoch, Batchsize, Learning Rate



ICT Express

Volume 6, Issue 4, December 2020, Pages 312-315



The effect of batch size on the generalizability of the convolutional neural networks on a histopathology dataset

Ibrahem Kandel 💍 🖾, Mauro Castelli

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https://doi.org/10.1016/j.icte.2020.04.010

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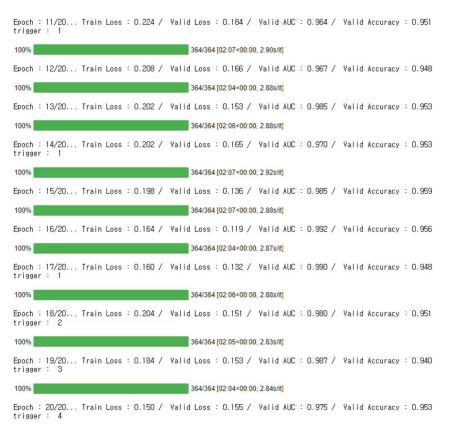
실험 결과

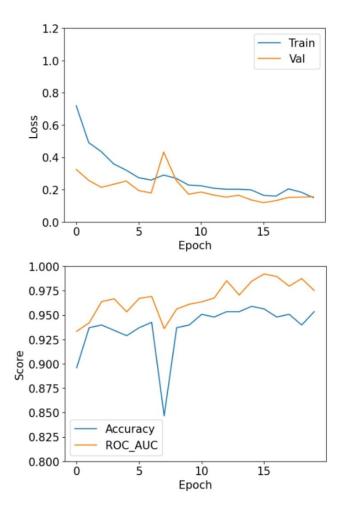
Test AUC		
Batch size	$Adam\ LR=0.0001$	$Adam\ LR=0.001$
16	0.9677	0.9144
32	0.9636	0.9332
64	0.9616	0.9381
128	0.9567	0.9432
256	0.9585	0.9652

Test AUC		
Batch size	$SGD\ LR = 0.0001$	$SGD\ LR = 0.001$
16	0.9555	0.9461
32	0.9570	0.9521
64	0.9512	0.9545
128	0.9302	0.9567
256	0.9077	0.9579



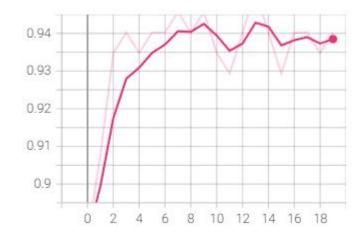
Resnet50

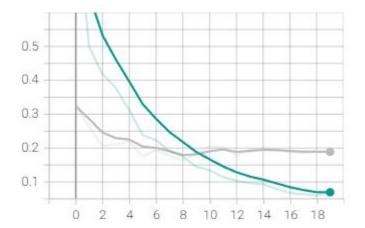




EfficientNet B0

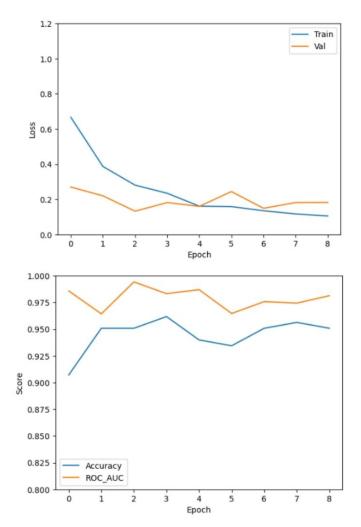
Epoch: 3/39 Train Loss: 0.419 Valid Loss: 0.207 Valid Accuracy: Epoch: 4/39 Train Loss: 0.377 Valid Loss: 0.210 Valid Accuracy:	0.886 0.908 0.935 0.940
trigger: 1 Epoch: 5/39 Train Loss: 0.311 Valid Loss: 0.220 Valid Accuracy:	0.935
trigger: 2 Epoch: 6/39 Train Loss: 0.238 Valid Loss: 0.176 Valid Accuracy: Epoch: 7/39 Train Loss: 0.223 Valid Loss: 0.195 Valid Accuracy: trigger: 1	
Epoch: 8/39 Train Loss: 0.191 Valid Loss: 0.177 Valid Accuracy:	0.946
Epoch: 9/39 Train Loss: 0.175 Valid Loss: 0.163 Valid Accuracy: Epoch: 10/39 Train Loss: 0.145 Valid Loss: 0.185 Valid Accuracy	0.940 0.946
trigger: 1 Epoch: 11/39 Train Loss: 0.135 Valid Loss: 0.204 Valid Accuracy	0.935
trigger: 2 Epoch: 12/39 Train Loss: 0.115 Valid Loss: 0.203 Valid Accuracy	0.929
trigger: 3 Epoch: 13/39 Train Loss: 0.103 Valid Loss: 0.178 Valid Accuracy	0.940
trigger: 4 Epoch: 14/39 Train Loss: 0.097 Valid Loss: 0.196 Valid Accuracy	0.951
trigger: 5 Epoch: 15/39 Train Loss: 0.093 Valid Loss: 0.200 Valid Accuracy trigger: 6	0.940
Epoch 00015: reducing learning rate of group 0 to 6.0000e-06.	
Epoch : 16/39 Train Loss : 0.079 Valid Loss : 0.193 Valid Accuracy trigger : 7	0.929
Epoch: 17/39 Train Loss: 0.068 Valid Loss: 0.188 Valid Accuracy trigger: 8	0.940
Epoch : 18/39 Train Loss : 0.064 Valid Loss : 0.186 Valid Accuracy	0.940
trigger: 9 Epoch: 19/39 Train Loss: 0.060 Valid Loss: 0.189 Valid Accuracy	0.935
trigger: 10 Epoch: 20/39 Train Loss: 0.069 Valid Loss: 0.188 Valid Accuracy	0.940





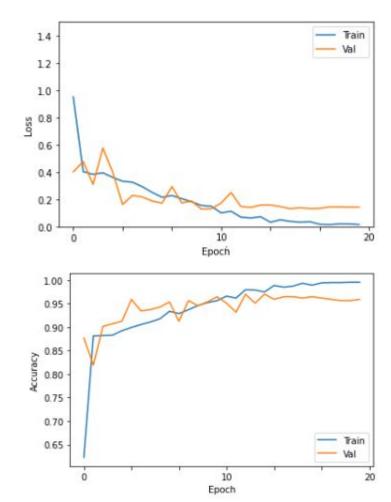
EfficientNet B4





EfficientNet B7

100% 409/410 [07:51<00:01, 1.13s/it]	
Epoch : 1/20 Train Loss : 0.670 Valid Loss : 0.207 Valid Accuracy	0.929
100%	
100%	
Epoch : 2/20 Train Loss : 0.368 Valid Loss : 0.204 Valid Accuracy	0.962
100%	
100%	
Epoch: 3/20 Train Loss: 0.272 Valid Loss: 0.181 Valid Accuracy	0.935
100% 	
Epoch: 4/20 Train Loss: 0.202 Valid Loss: 0.188 Valid Accuracy	0.946
trigger: 1	
100%	
Epoch : 5/20 Train Loss : 0.149 Valid Loss : 0.254 Valid Accuracy	0.940
trigger: 2	
100% 	
Epoch : 6/20 Train Loss : 0.119 Valid Loss : 0.242 Valid Accuracy	0 946
trigger: 3	0.040
100% 	
Epoch : 7/20 Train Loss : 0.111 Valid Loss : 0.242 Valid Accuracy	0.040
trigger: 4	0.340
100% 410/410 [08:04<00:00, 1.18s/it]	
Epoch : 8/20 Train Loss : 0.094 Valid Loss : 0.158 Valid Accuracy	0.962
	0.302
100% 410/410 [08:07<00:00, 1.19s/it]	0.051
Epoch : 9/20 Train Loss : 0.083 Valid Loss : 0.244 Valid Accuracy	: 0.951
trigger: 1	
100%	
Epoch : 10/20 Train Loss : 0.057 Valid Loss : 0.316 Valid Accuracy	: 0.918
trigger: 2	
100%	
Epoch : 11/20 Train Loss : 0.061 Valid Loss : 0.204 Valid Accuracy	: 0.951
trigger: 3	
100%	
Epoch : 12/20 Train Loss : 0.049 Valid Loss : 0.341 Valid Accuracy	: 0.924
trigger : 4	
100%	
Epoch : 13/20 Train Loss : 0.054 Valid Loss : 0.282 Valid Accuracy	: 0.935
trigger: 5	
100%	
Epoch : 14/20 Train Loss : 0.043 Valid Loss : 0.202 Valid Accuracy	: 0.967





ResNet50



submission_resnet50_e15_rrp.csv

Complete (after deadline) - 1s to go - resnet50 e15 rrp

0.95265

0.96257

EfficientNet B0



EfficientNet_B0 - Version 5

Complete (after deadline) - 1s to go

0.92975

0.93912

EfficientNet B4



subm_effnetb4.csv

Complete (after deadline) - 1s to go - effnetb4 rrp

0.94344

0.94252

EfficientNet B7

Submission and Description

Private Score (i)

0.9303

Public Score (i)

0.95338

Selected

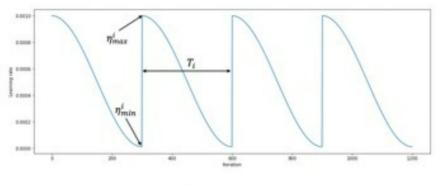
submission_test_Eff_B07.csv

Complete (after deadline) · now · Eff_B07 submission



옵티마이저 변경 최적의 파라미터 선정 (epoch, scheduler, batch_size..) 이미지 크기 조절

스케쥴러 교체



[그림2] Cosine annealing

```
optimizer = torch.optim.AdamW(model.parameters(), Ir=0.0001)
scheduler = CosineAnnealingWarmRestarts(optimizer,T_0=5, T_mult=1, eta_min=0.00001)
```

ResNet50



Complete (after deadline) · 18h ago · plant-pathology-ResNet50_e15_AdamW_CosineALR_bsize4_rl0001

0.95198

0.96613

EfficientNet B0



subm_effnetb0_cosine.csv

Complete (after deadline) - 1s to go - b0 cosine

0.92897

0.94362

EfficientNet B4



subm_effnetb4_cosineAlr.csv

Complete (after deadline) · 13h ago · plant-pathology-EfficientNetB4_e30_AdamW_CosineALR

0.9303

0.94252

EfficientNet B7



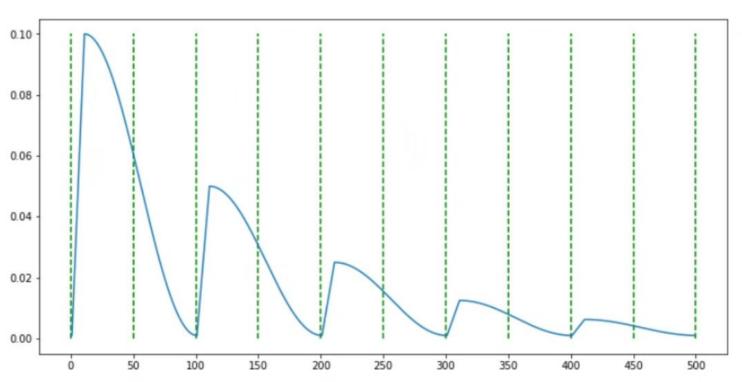
subm_effnetb7_cosineAlr.csv

Complete (after deadline) - 14h ago - plant-pathology-EfficientNetB7_e15_AdamW_CosineALR

0.95086 0.95878

추가 개선사항

$Custom\ Cosine Anneling Warm Restart$



추가 개선사항

모델별 권장 이미지 크기

	Model	Recommended Image Size
	ВО	224
	B1	240
	B2	260
EfficientNet V1	В3	300
	B4	380
	B5	456
	В6	528
	В7	600
	S	384
	M한글	480
EfficientNet V2	L	480
	ВО	224
	B1	240
	B2	260
	В3	300

