Assignment 2
Skin Lesion Classification

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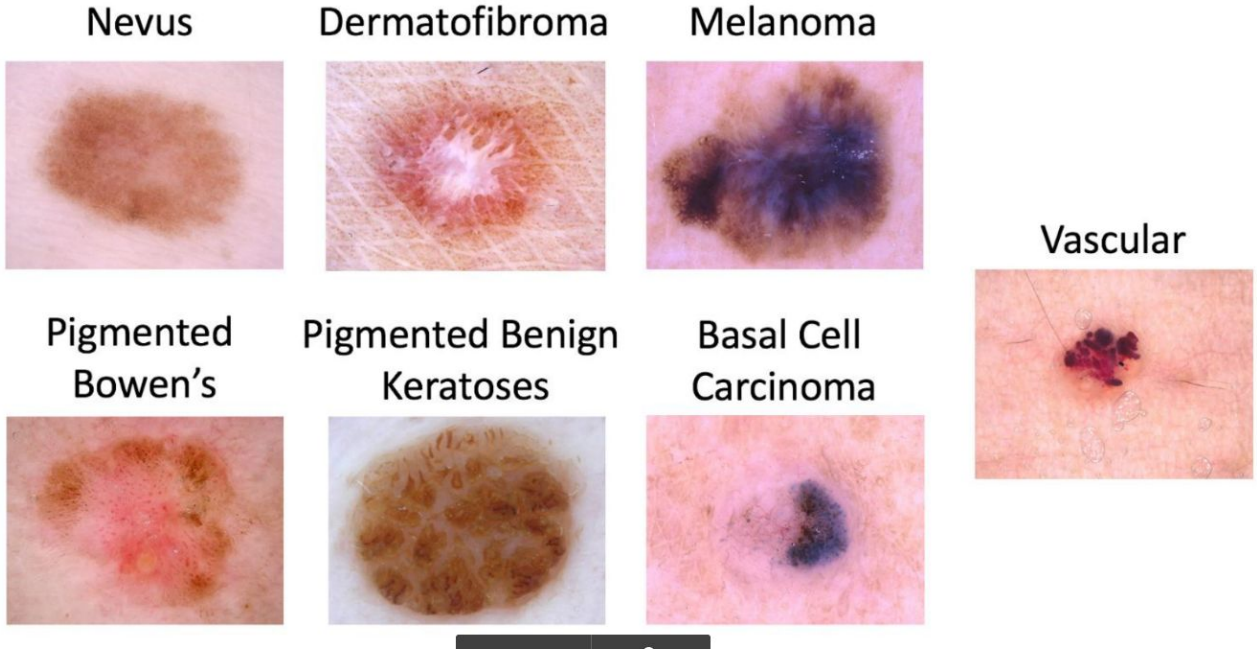
Task - Multi Class Classification



Network Architecture

ISIC Challenge 2018 Leaderboards

TASK 1: LESION BOUNDARY SEGMENTATION | TASK 2: LESION ATTRIBUTE DETECTION | TASK 3: LE

Rank <140 total> ↑	Team (Submitter User) <77 unique teams>	Approach Name	Manuscript
1	MetaOptima Technology Inc. *(Jordan Yap)*	Top 10 Models Averaged	
2	MetaOptima Technology Inc. *(Jordan Yap)*	Meta Ensemble	
3	MetaOptima Technology Inc. *(Jordan Yap)*	Best Single Model	

https://challenge2018.isic-archive.com/leaderboards/

TABLE II
MODELS USED IN ENSEMBLE

Model	Input Size	Loss	Balanced Accuracy
DPN-92(5k)	224×224	0.331	0.787
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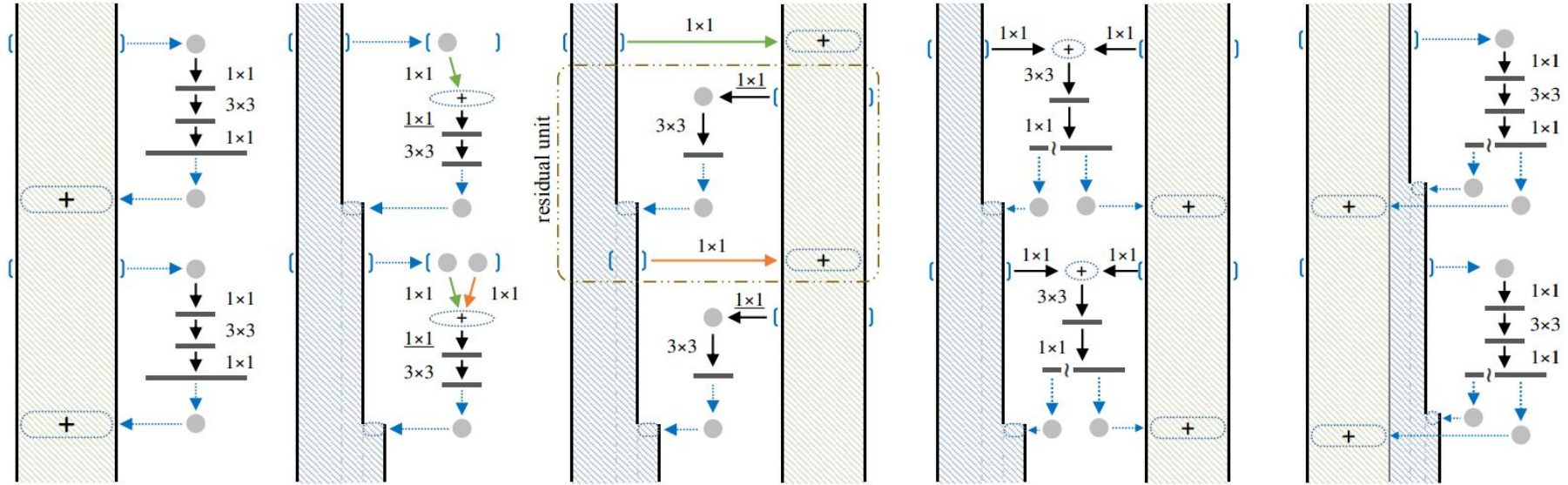
Resnet-152	224×224	0.333	0.770
Densenet-161	224×224	0.334	0.771
Inceptionv3	299×299	0.334	0.770
Inceptionv3*	299×299	0.359	0.757
seresneXt-50	224×224	0.345	0.774
ResNet-50	224×224	0.350	0.772
ResNet-34	224×224	0.356	0.762
ResNet-34	224×224	0.358	0.759
ResNet-50**	224×224	0.364	0.766
seresneXt-50†	224×224	0.366	0.793
seresneXt-50†	224×224	0.372	0.801
seresnet-50	224×224	0.393	0.720
ResNet-18	224×224	0.381	0.736
ResNet-50	224×224	0.437	0.721
ResNet-18‡	224×224	0.438	0.774
Squeezenet1.1	224×224	0.558	0.555
histogram	NA	0.797	0.323

Network Architecture - Dual Path Network (DPN)



The residual path implicitly reuses features, but it is not good at exploring new features.

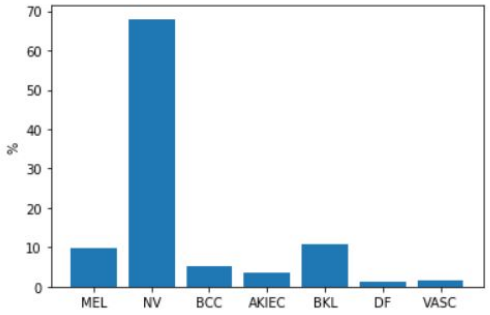
The densely connected network keeps exploring new features but suffers from higher redundancy.

Paper:
https://arxiv.org/abs/1707.01629

Pretrained model:
https://github.com/Cadene/pretrained-models.pytorch

Handling Imbalance

Train Set Statistics




```
MEL, count: 887, 9.84%
NV, count: 6130, 68.00%
BCC, count: 480, 5.32%
AKIEC, count: 317, 3.52%
BKL, count: 972, 10.78%
DF, count: 101, 1.12%
VASC, count: 128, 1.42%
```

a) Sampling:

1) Undersampling
2) **Oversampling**

Balanced Mini Batch

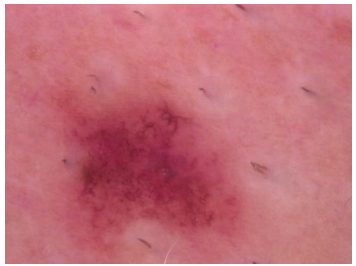
MEL	NV	BCC	AKIEC	BKL	DF	VASC

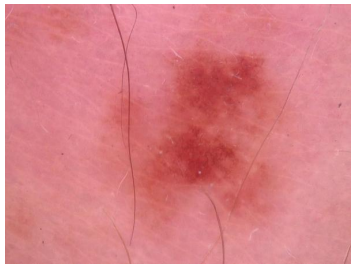
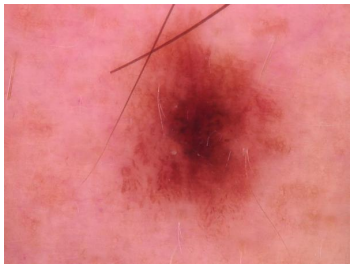
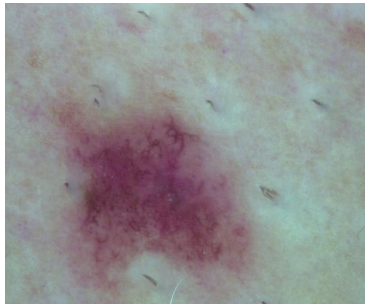
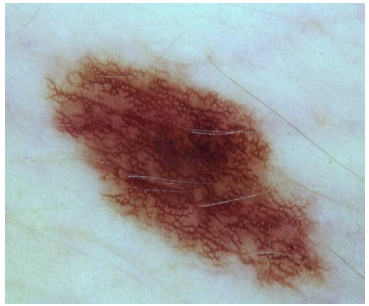
Batch size 7, 14, or 21 etc.

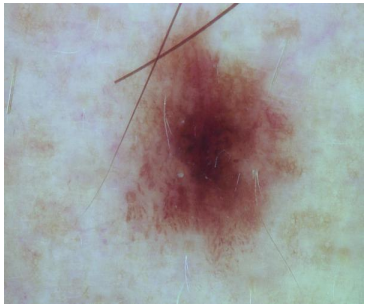
b) Weighted loss

$$-w_0 y log(p) - w_1(1-y)log(1-p)$$

Color Constancy





What would the image look like if it was taken under white light
(Under Gray World Assumption)

https://ieeexplore.ieee.org/document/6866131

Augmentations

- HorizontalFlip(),
- RandomRotate90(),
- RandomBrightnessContrast(

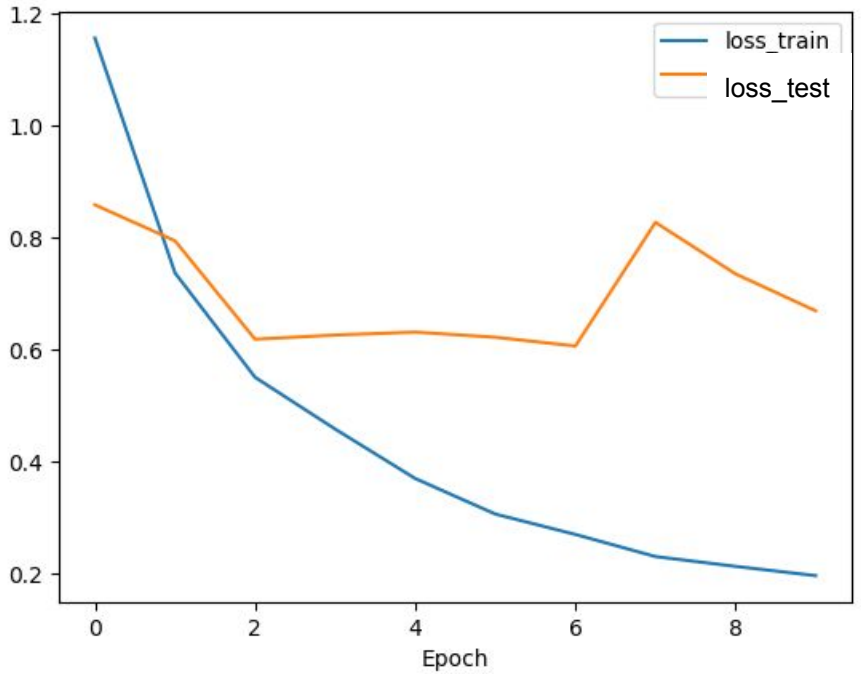
  brightness_limit= [-0.2, 0.2],

  contrast_limit=[-0.2, 0.2]),
- RandomCrop(400, 400, p=0.5),
- Resize(256, 256),
- Normalize() (mean and std taken from imagenet)

Training parameters

- Epoch number : 10
- Batch size: 21-24
- Learning rate: 0.00001
- Loss function: (Weighted) Cross Entropy
- Loss weights: [0.8, 0.2, 1.0, 1.0, 0.8, 1.0, 1.0]
- Optimizer: adam
- Network depth: 92 trainable layers
- Input number of channels: 3
- Output number of channels: 7
- OS: Windows
- GPU: RTX 2070

Loss Plot



Results - (Accuracy)

Sampling → Random (RS), Balanced Sampling (BS)

Color → Original Color (OC), Color Constancy (CC)

Loss → Weighted Loss(WL), Unweighted Loss (UL)

RS+WL+ OC	BS+UL+ OC	RS+WL+ CC	BS+UL+ CC
0.8200	0.8260	0.8280	0.7880

Accuracy measured at minimum test loss

Metrics

Accuracy: 0.8280

Recall: 0.7820

Precision: 0.7720

Confusion matrix

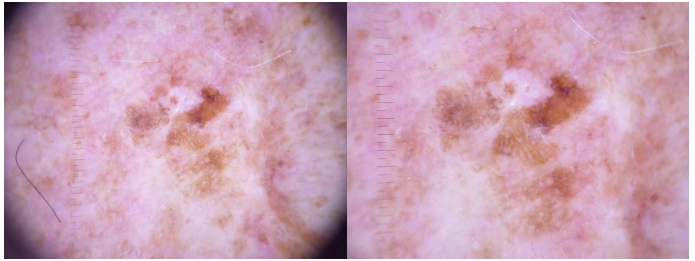
Conclusion

A few duplicate images in the train set.

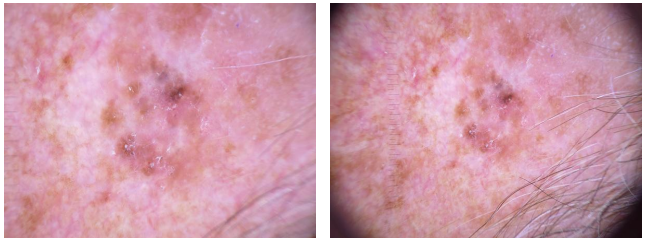
Better Hyper parameter tuning

Exploring more architectures

More advance techniques, few shot learning or meta learning can be explored for rare diseases.



ISIC_0025030 ISIC_0027419



ISIC_0026769 ISIC_0025661

Duplicates