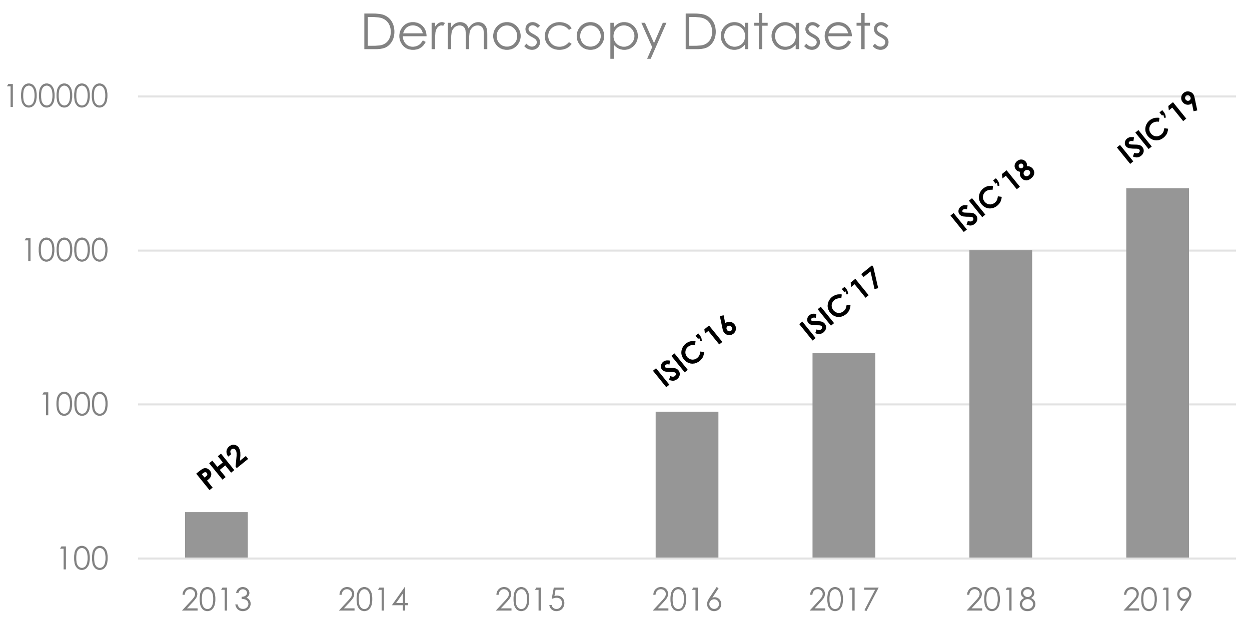
How Important Is Each Dermoscopy Image?

Catarina Barata and Carlos Santiago

Motivation

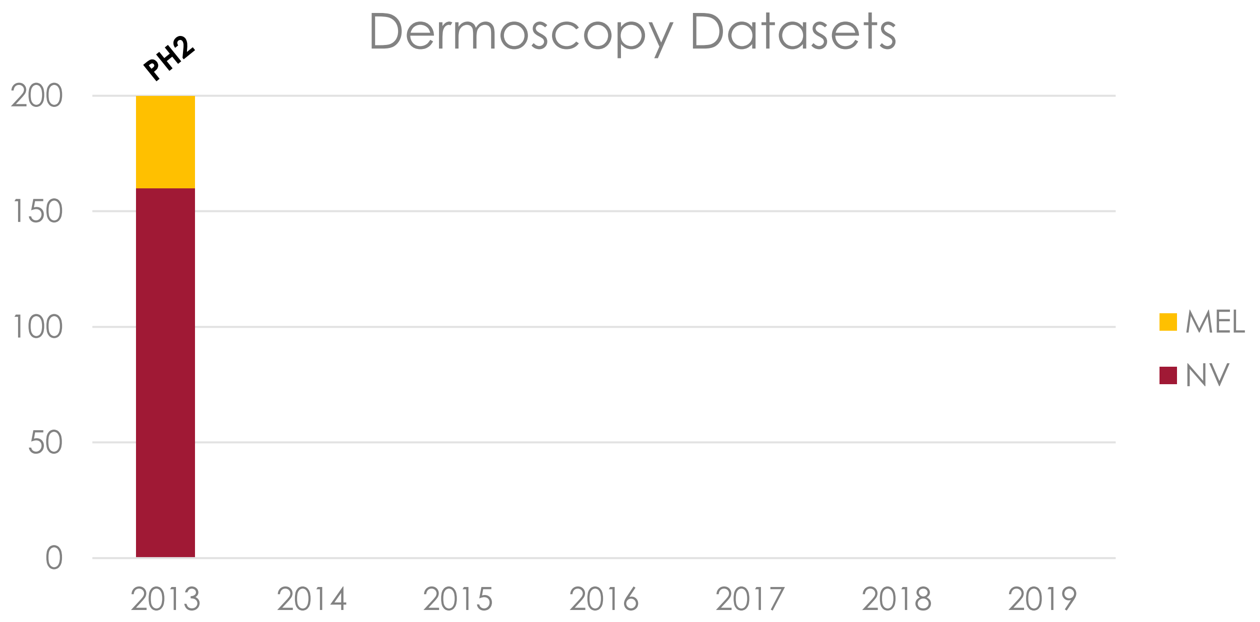

Dermoscopy Datasets
100000
10000
1000
100
PH2
ISIC'16
ISIC'17
ISIC'18
ISIC'19
2013
2014
2015
2016
2017
2018
2019

Motivation

Deep
Networks
Like
Data

Motivation

Class Distribution



Motivation

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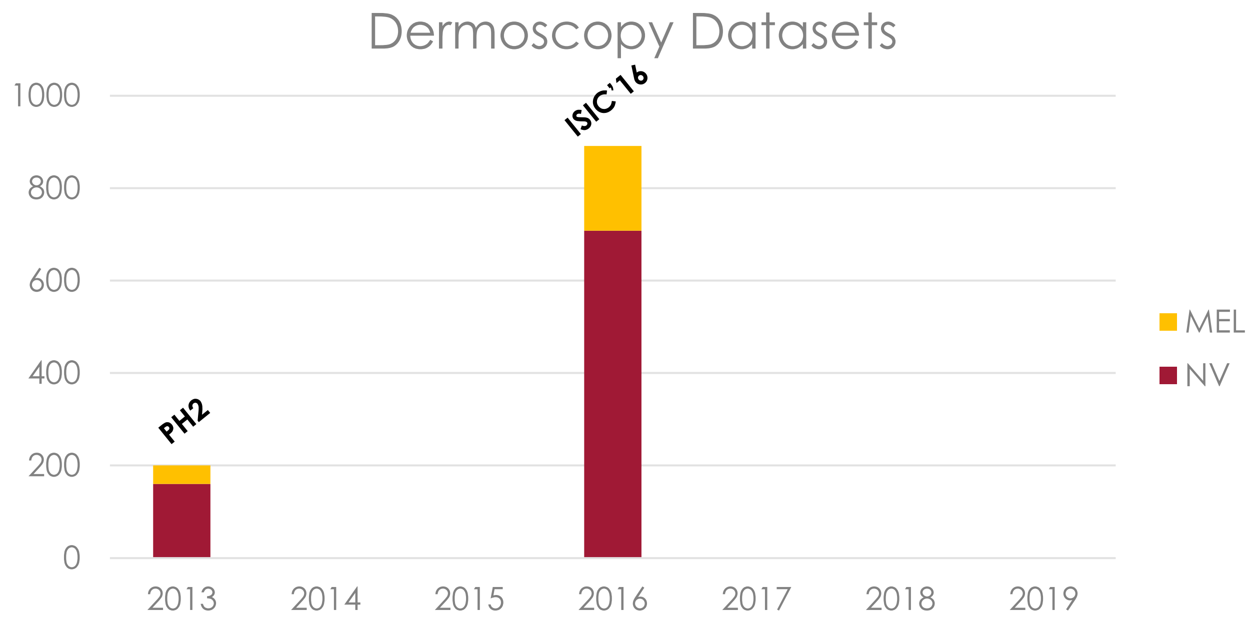
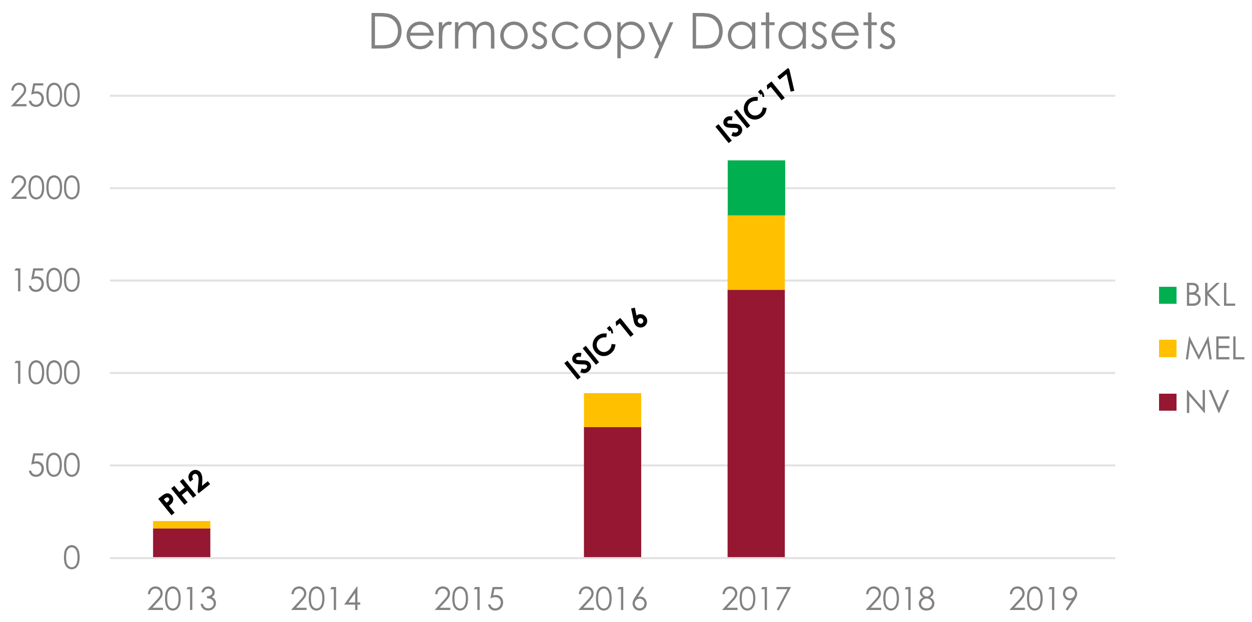


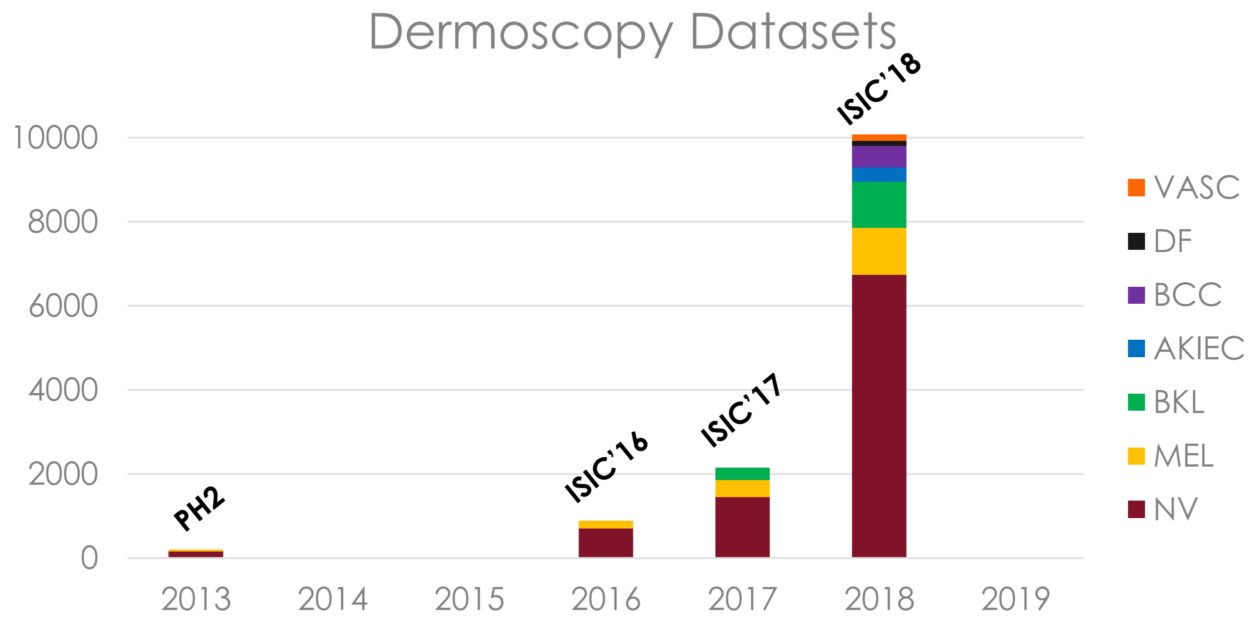
Motivation

Class Distribution



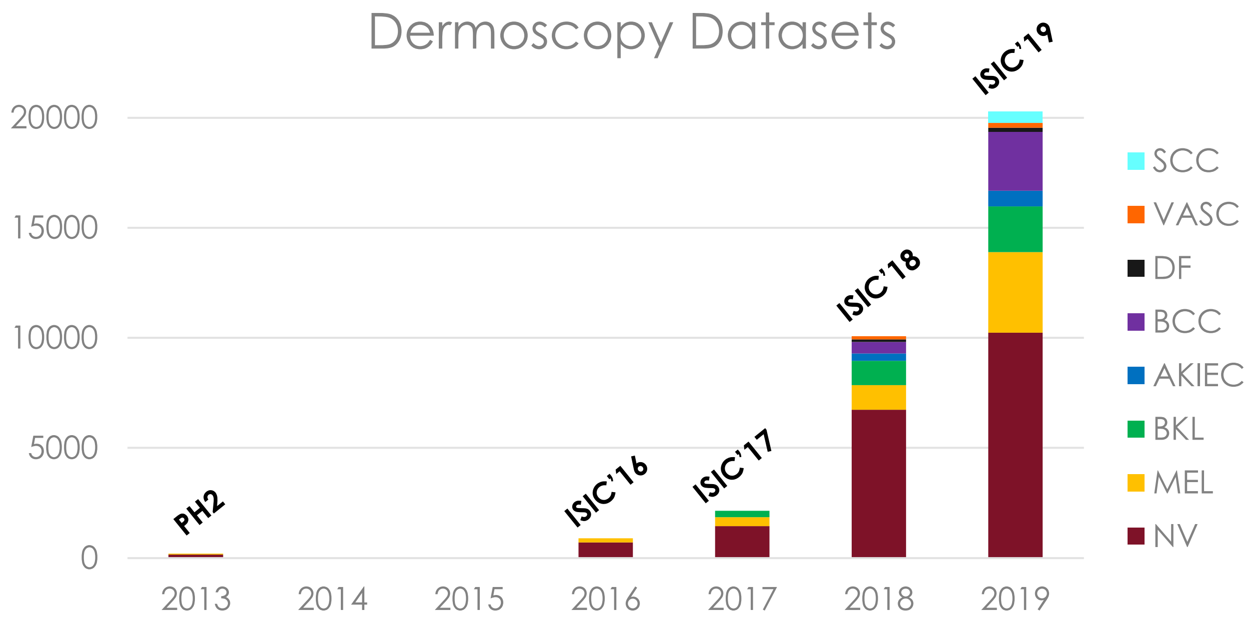
Motivation

Class Distribution



Motivation

Class Distribution

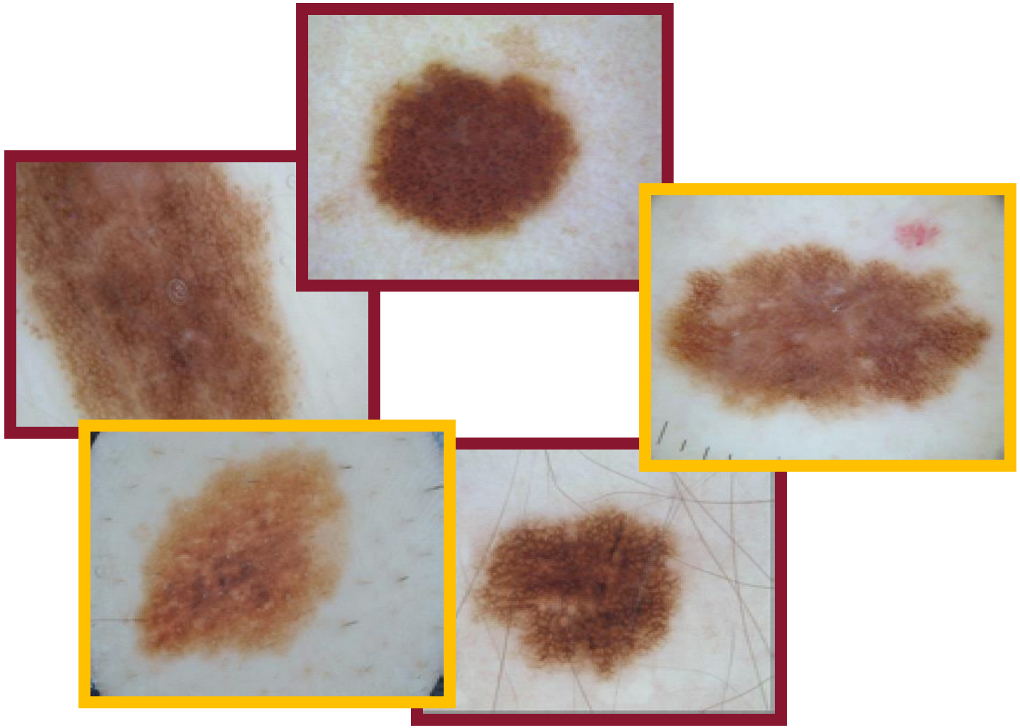


Motivation

Why is this a problem?

- Network bias
- Poor Generalization

Class	# Samples	Deep Net Recall (%)
NV	6741	95
MEL	1119	66
BKL	1101	77
AKIEC	331	45
BCC	517	88
DF	116	43
VASC	143	68



Me Likes Balanced Data More...

Challenges

- Deal with class imbalance
- Not all classes are equally hard
- Are all samples equally important?

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Goal

How to make the most of the available data?

- Data Augmentation
- Importance Sampling
- Sample Weighting

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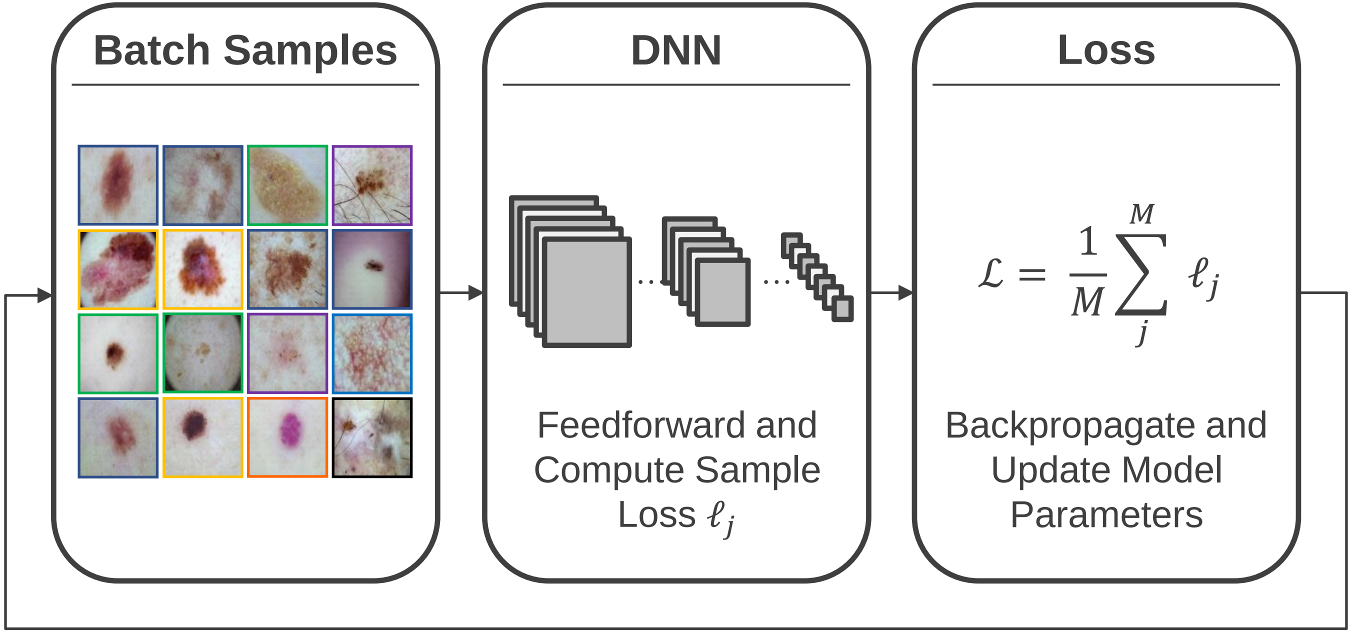
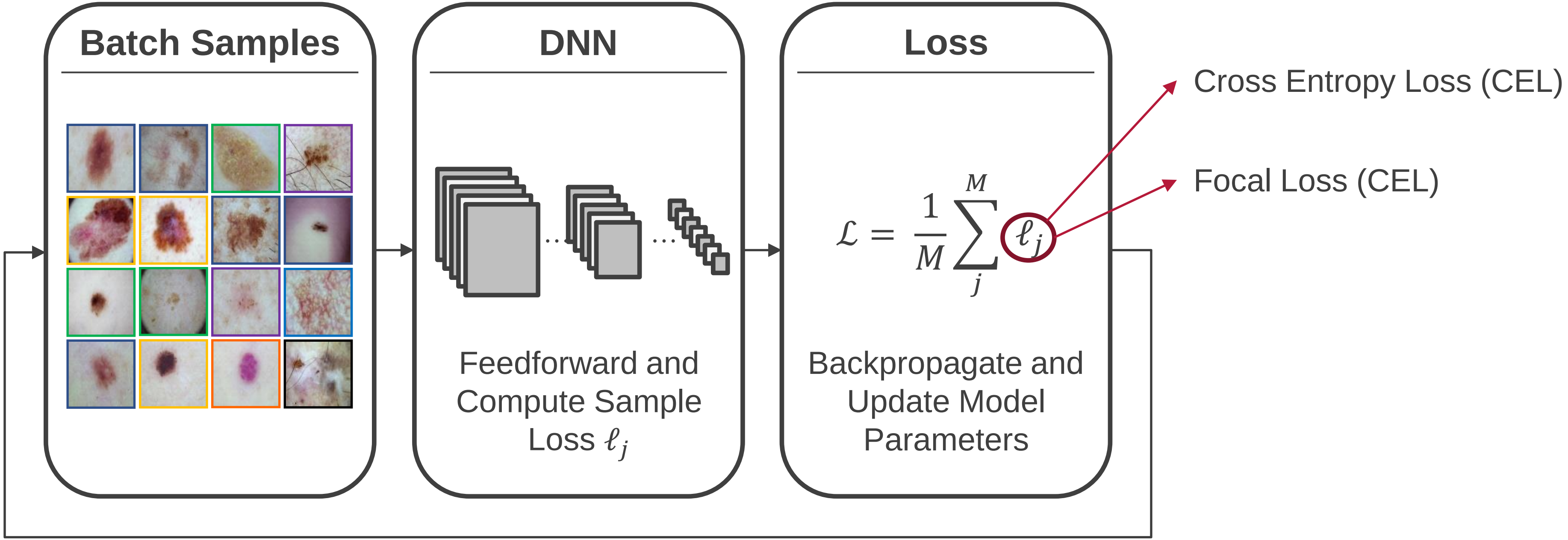
- **Sample Weighting**

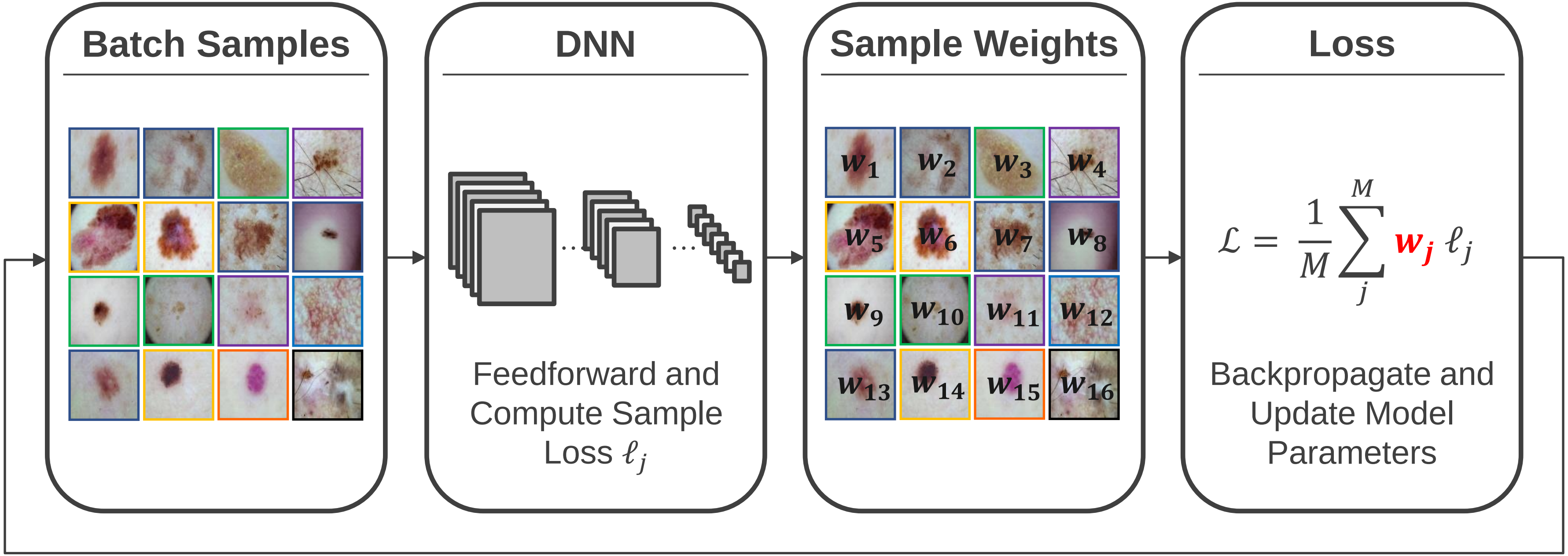
Sample Weighting



Sample Weighting



Sample Weighting



Weighting Strategies

- Class-Balanced Losses
  - Class-balanced (CB)[1]:

$$w_j = \frac{N}{N_{y_j}}$$

  - Effective Number of Samples (ES)[2]:

$$w_j = \frac{1-\beta}{1-\beta^{N_{y_j}}}, \qquad \beta = \frac{N-1}{N}$$

[1] Provost, *Machine Learning From Imbalanced Datasets 101*, AAAI 2000
[2] Cui et al., *Class-balanced Loss Based on Effective Number of Samples*, CVPR 2019

Weighting Strategies

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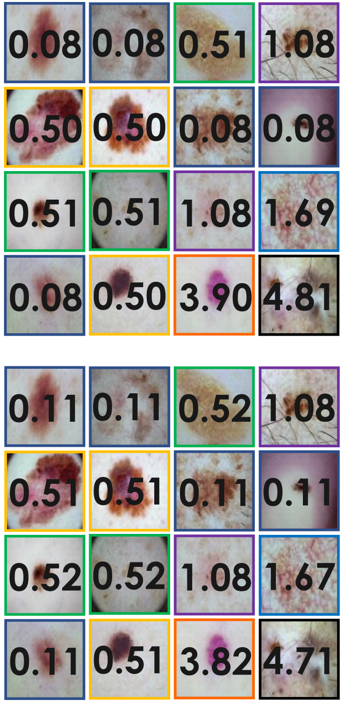

Weighting Strategies

- Curriculum Learning

$$\arg\min_{\boldsymbol{w}} \frac{1}{M} \sum_{j}^{M} w_j \, \ell_j + G(\boldsymbol{w}; \lambda)$$

Weighting Strategies

- Curriculum Learning
  - Self-paced Learning (SPL)[1]:

$$G(\boldsymbol{w};\lambda) = -\lambda||\boldsymbol{w}||_1$$

  - Online Hard Example Mining (OHEM)[2]:

$$G(\boldsymbol{w};\lambda) = +\lambda||\boldsymbol{w}||_1$$

[1] Kumar et al., *Self-Paced Learning for Latent Variable Models*, NeurIPS 2010
[2] Shrivastava et al., *Training Region-based Object Detectors with Online Hard Example Mining*, CVPR 2016

Weighting Strategies

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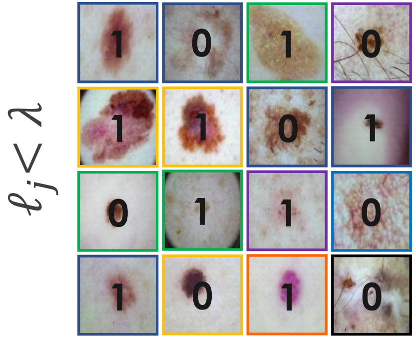
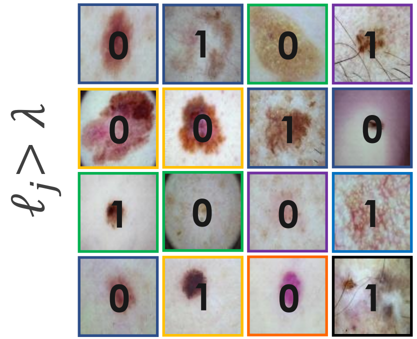




Experimental Setup

- DNN Architectures
  - Flat Classifier (VGG-16)
  - Hierarchical Classifier[1]

  + CBAM[2]
- Dataset
  - ISIC 2018
- Performance Metrics
  - Recall
  - Precision
  - F1-Score
  - Accuracy
  - Balanced Accuracy

[1] Barata et al., *Explainable Skin Lesion Diagnosis Using Taxonomies*, Pattern Recognition 2020
[2] Woo et al., *CBAM: Convolutional Block Attention Module*, ECCV 2018

Results

	Loss	Acc	BAcc	mPR	mF1
CEL	-	87.5	75.5	80.0	77.0
FL	-	87.0	74.5	79.0	76.0

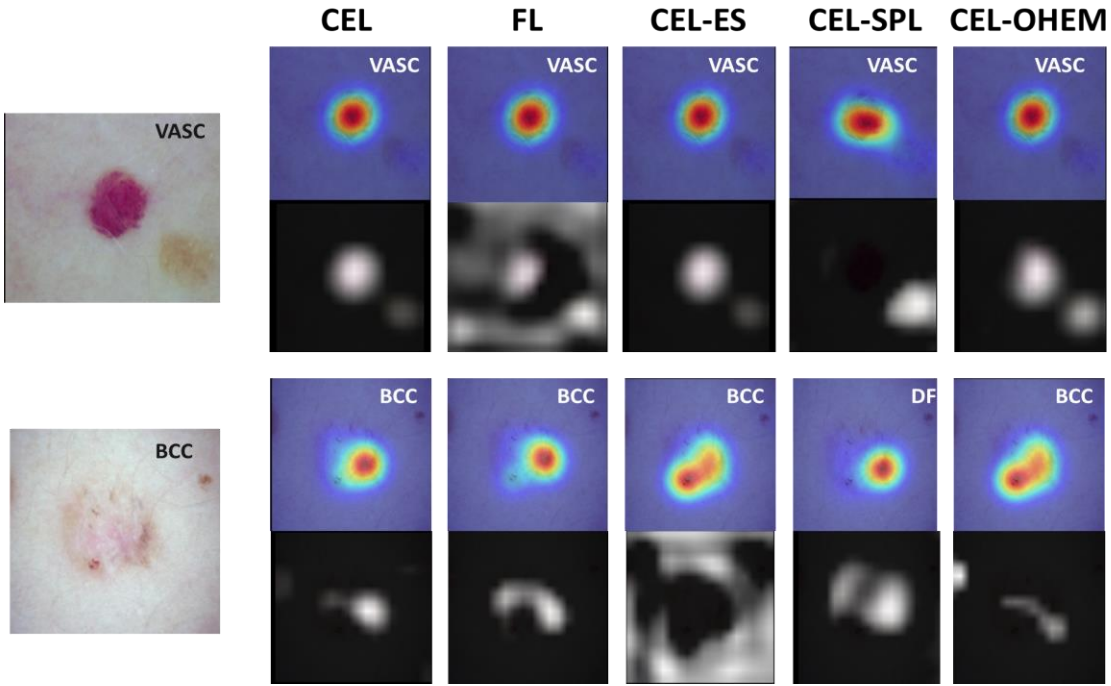
Results

	Loss	Acc	BAcc	mPR	mF1
CEL	-	87.5	75.5	80.0	77.0
	CB	84.0	78.4	76.0	76.5
	ES	84.5	76.7	77.0	76.0
FL	-	87.0	74.5	79.0	76.0
	CB	83.0	76.9	73.0	75.0
	ES	83.5	78.0	74.0	75.5

Results

	Loss	Acc	BAcc	mPR	mF1
CEL	-	87.5	75.5	80.0	77.0
	CB	84.0	78.4	76.0	76.5
	ES	84.5	76.7	77.0	76.0
	SPL	85.5	68.8	76.5	72.0
	OHEM	87.0	76.4	79.0	76.5
FL	-	87.0	74.5	79.0	76.0
	CB	83.0	76.9	73.0	75.0
	ES	83.5	78.0	74.0	75.5
	SPL	84.5	65.3	71.5	67.5
	OHEM	88.0	75.7	80.5	77.5

Results


CEL
FL
CEL-ES
CEL-SPL
CEL-OHEM
VASC
VASC
VASC
VASC
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VASC
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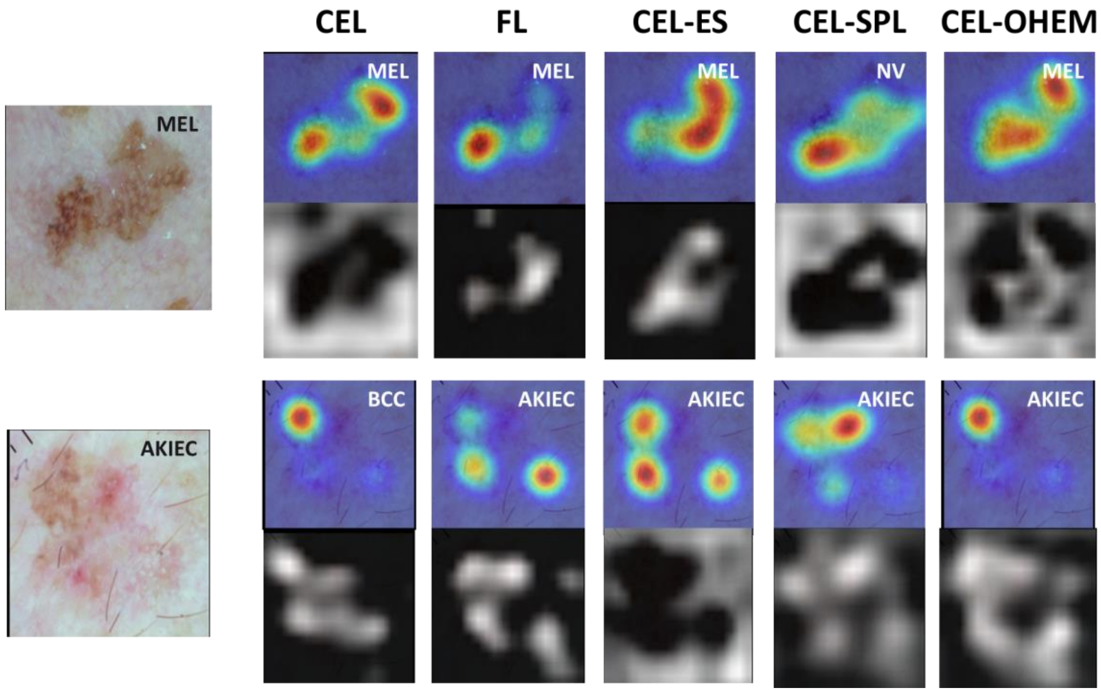
BCC
BCC
BCC
DF
BCC

Results


CEL
FL
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CEL-OHEM
MEL
MEL
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NV
MEL
AKIEC
BCC
AKIEC
AKIEC
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AKIEC

Conclusions

- Weighting strategies significantly affect the performance of a DNN
- Some weighting schemes may induce bias
- Features learned by DNNs change according to the learning strategy
- OHEM achieves the best overall performance

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Thank You!

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