universidade de aveiro
departamento de eletrónica,
telecomunicações e informática

Deep learning for multi-class skin lesion diagnosis

Fábio Miguel Tomaz dos Santos

Supervisors: Filipe Silva, Pétia Georgieva

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Structure

1. **Motivation and Objectives**
2. CNNs and Transfer Learning
3. Experimental Setup
4. Pre-trained Model Choice and Hyperparameter Tuning
5. Improving the Model’s Generalization Performance
6. Results Discussion and Comparison
7. Conclusion

Background and Motivation

- The **International Skin Imaging Collaboration** challenges provides a **benchmark** for comparison of skin lesion classifiers:
  - Yearly challenges since 2016
  - The problem is not solved!
- **Convolutional Neural Network (CNN) models** present state-of-the-art performance in these type of challenges
- **Several Limitations** prevent these models from achieving better generalization performance:
  - Data limitations
  - Hardware limitations
  - Divergent train and test set distributions

Objectives

- To respond to the **ISIC 2019 challenge** by studying methods to **improve the generalization performance** of classifiers of multiple types of skin lesions
- To focus on **Convolutional Neural Network (CNN) architectures** and **transfer learning** as well as the impact of (8-class classifier):
  - **Data augmentation**
  - **Class balancing**
  - **Ensemble learning**
- To compare different strategies to identify **out of training distribution samples** from the test set (9-class classifier)

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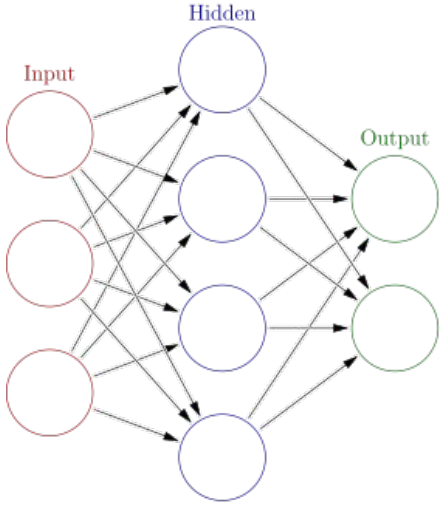
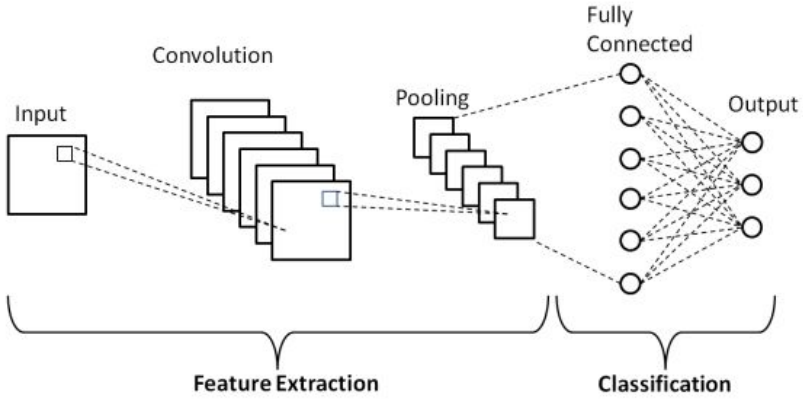
Artificial Neural Networks and Deep Learning

- Artificial Neural Network (ANN):
  - **Input layer, hidden layer, and output layer**
  - Layers composed by **neurons**
  - Activation functions (e.g., ReLU, softmax)
  - **Optimization strategy** to minimize the loss (*e.g.*, SGD, Adam)
  - **Loss function** (*e.g.*, cross entropy loss)
- Deep neural network:
  - More hidden layers
  - Can build levels of abstraction
  - **No need for feature engineering**



Convolutional Neural Networks (CNNs)

- Deep learning topology
- Used for image classification problems
- Structure:
  - Convolutional base
  - Classifier
- Distinguishing concepts:
  - **Local receptive fields** - local features
  - **Shared weights** - translation invariance
  - **Pooling layers** - information summary



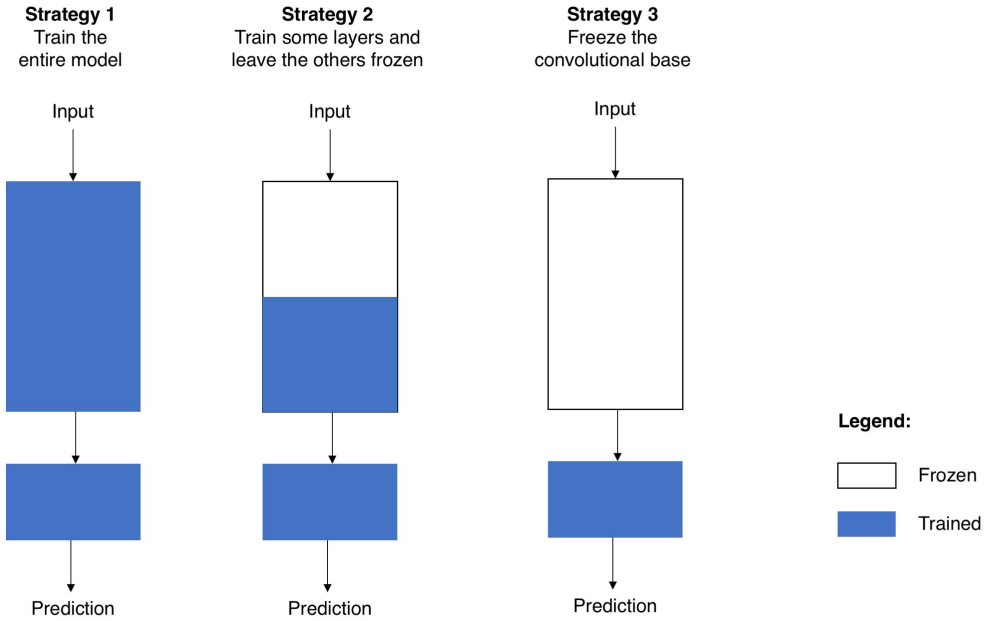
CNN Architectures

- **AlexNet:** CNN breakthrough
- **VGG:** representational depth leap
- **ResNet:** solved the vanishing gradients problem
- **DenseNet:** extended ResNet concepts
- **Inception:** Highly engineered architecture
- **EfficientNet:** Compound scaling method

Model	Year	Size	Top-1 Accuracy	Top-5 Accuracy	Params (Millions)	Depth	Input Size
AlexNet	2012	238 MB	0.570	0.803	≈ 60	8	256x256
VGG16	2014	528 MB	0.713	0.901	≈ 138	16	224x224
VGG19	2014	549 MB	0.713	0.900	≈ 143	19	224x224
ResNet50	2015	98 MB	0.749	0.921	≈ 26	50	224x224
ResNet101	2015	171 MB	0.764	0.928	≈ 45	101	224x224
ResNet152	2015	232 MB	0.766	0.931	≈ 60	152	224x224
DenseNet121	2016	33 MB	0.750	0.923	≈ 8	121	224x224
DenseNet169	2016	57 MB	0.762	0.932	≈ 14	169	224x224
DenseNet201	2016	80 MB	0.773	0.936	≈ 20	201	224x224
InceptionV3	2015	92 MB	0.779	0.937	≈ 24	159	299x299
InceptionResNetV2	2016	215 MB	0.803	0.953	≈ 56	572	299x299
EfficientNetB0	2019	5.3 MB	0.773	0.935	≈ 5	NA	224x224
EfficientNetB1	2019	7.9 MB	0.792	0.945	≈ 8	NA	240x240
EfficientNetB2	2019	9.2 MB	0.803	0.950	≈ 9	NA	260x260
EfficientNetB3	2019	12.3 MB	0.817	0.956	≈ 12	NA	300x300
EfficientNetB4	2019	19.5 MB	0.830	0.963	≈ 19	NA	380x380
EfficientNetB5	2019	30.6 MB	0.837	0.967	≈ 30	NA	456x456
EfficientNetB6	2019	43.3 MB	0.842	0.968	≈ 43	NA	456x456
EfficientNetB7	2019	66.7 MB	0.844	0.971	≈ 66	NA	600x600

Transfer Learning

- **Reusing a pre-trained model's knowledge for another related task**
- Alleviates the lack of data;
- Replace the classifier;
- Different strategies to deal with the convolutional base:
  - How large is the dataset?
  - How similar are the datasets?
  - What is the available computational capability?



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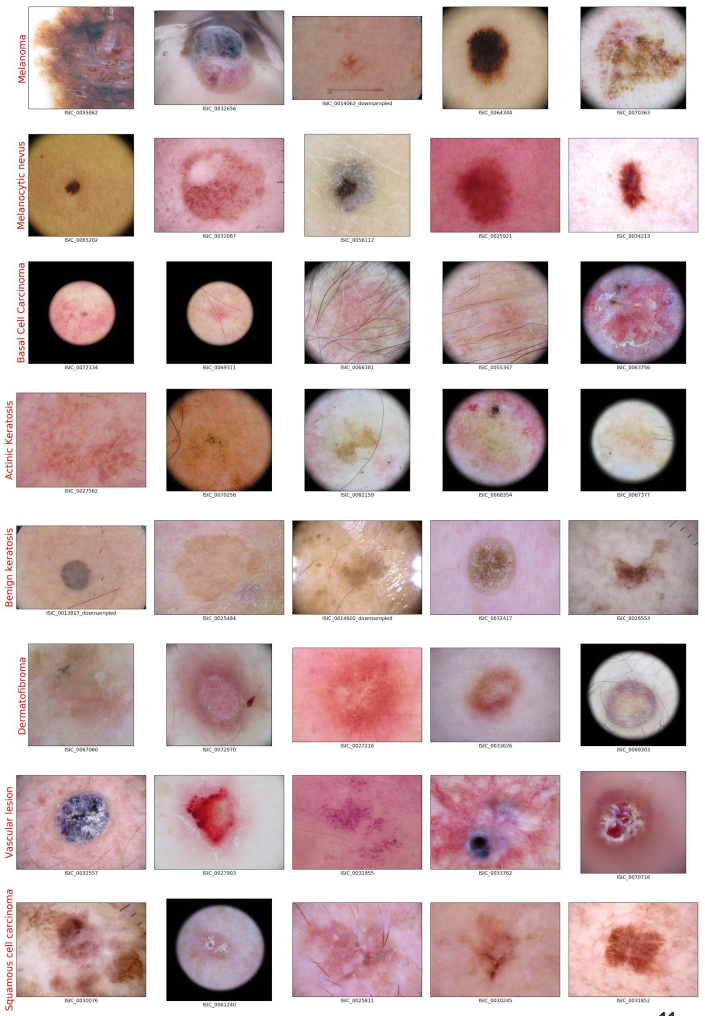
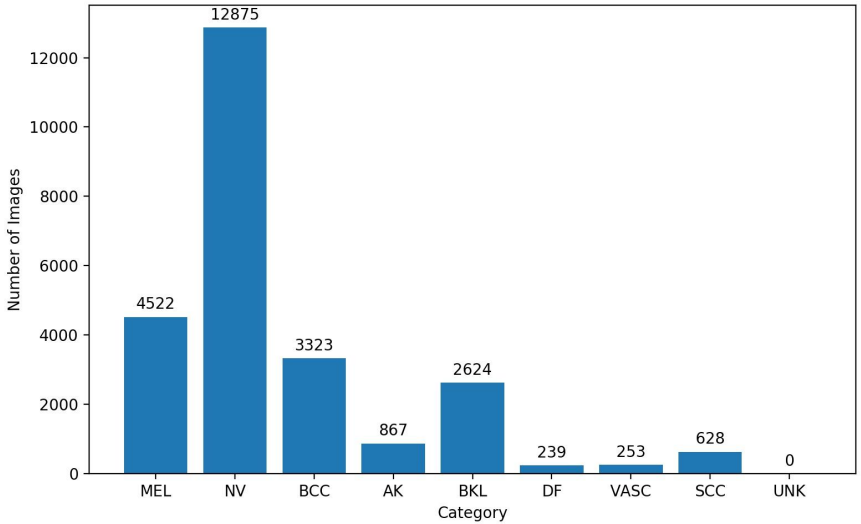
ISIC 2019 Dataset

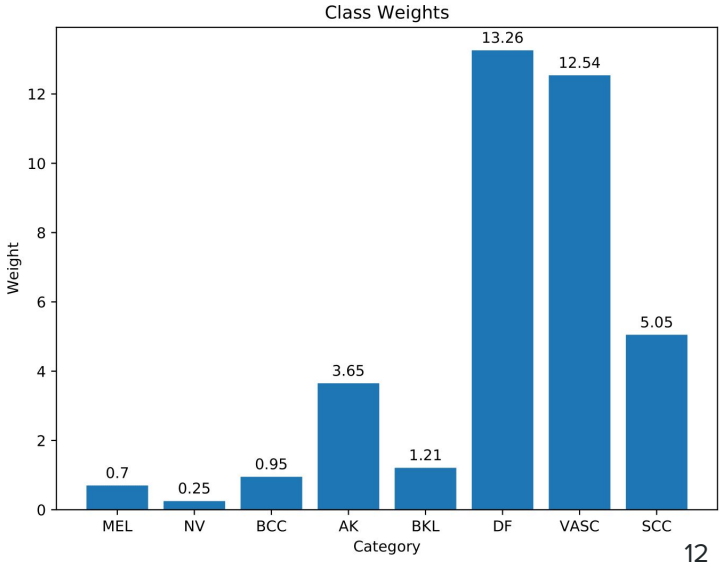
- Contains **8 classes**:
  - Melanoma (MEL)
  - Melanocytic nevus (NV)
  - Basal cell carcinoma (BCC)
  - Actinic keratosis (AK)
  - Benign keratosis (BK)
  - Dermatofibroma (DF)
  - Vascular lesion (VASC)
  - Squamous cell carcinoma (SCC)
- Pre-processing: **cropping**, **resizing**, **normalization**
- Train, validation and test split
- **Same validation & test sets across experiments**



Class Imbalance

- **High imbalance leads to poor optimization strategies**
- Solution: Assign higher loss towards underrepresented classes in the loss function





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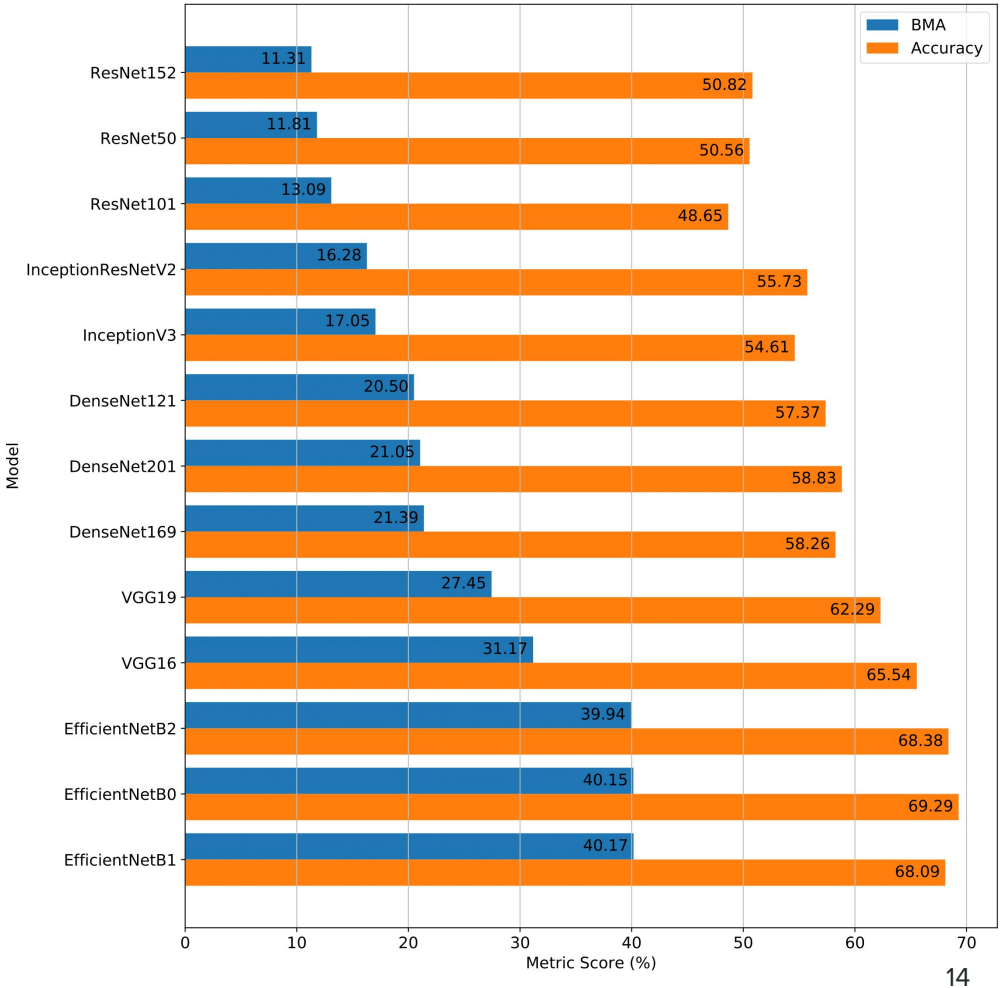
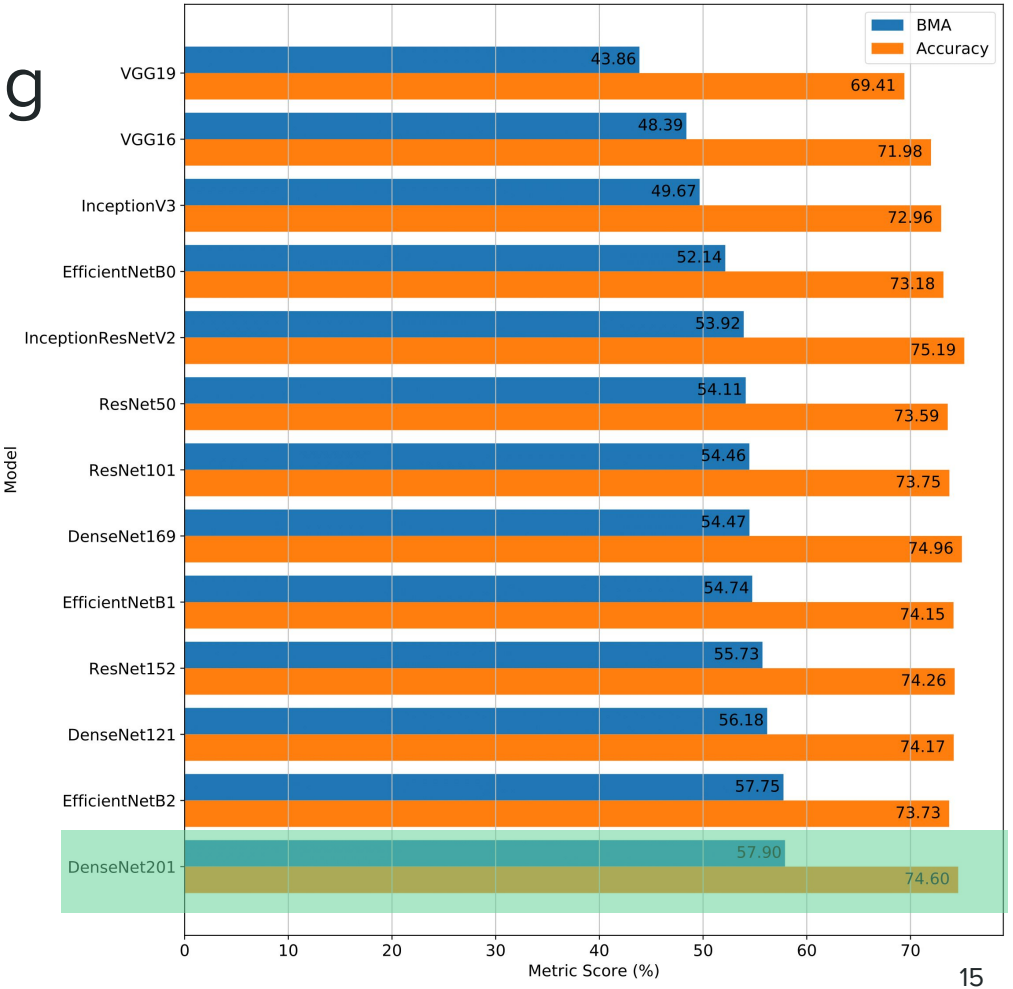
Freeze the Convolutional Base

- ImageNet is substantially different from ISIC 2019
- Convolutional base parameters are optimized for a very specific domain
- Relatively good performance on EfficientNets
- **Sub-optimal transfer learning approach for skin lesion classification!**



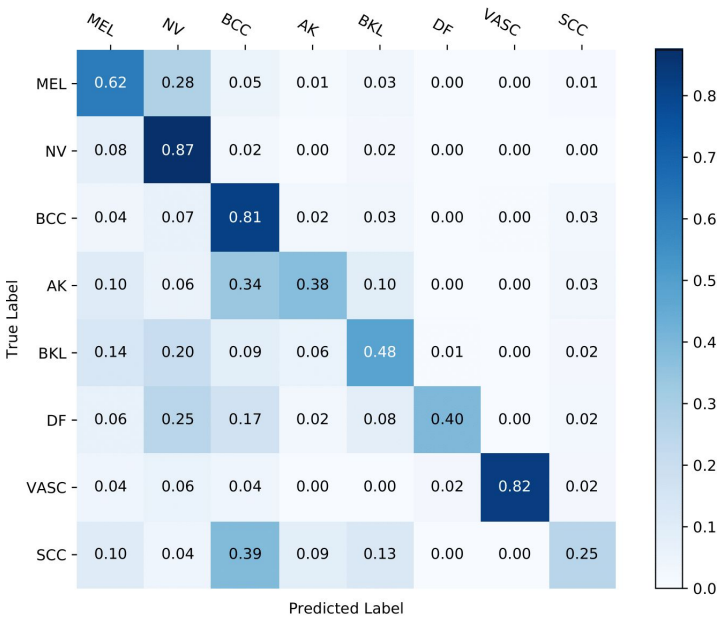
Extraction and Fine-tuning of Convolutional Layers

- **Knowledge obtained from the existing weights will be adapted to a new problem**
- **Recent architectures outperform old ones**
- Representational depth is beneficial
- Remarkable EfficientNet scalability!
- **The DenseNet201 is selected for future experiments.**

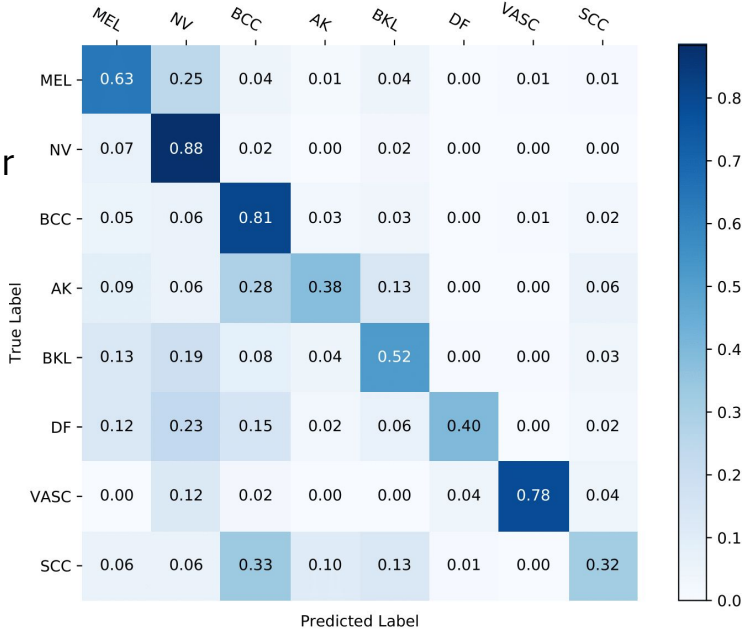


Performance Evaluation

- Poor generalization performance on underrepresented classes
- Hyperparameter optimization barely made an improvement
- **Pre-trained models are well adapted for a wide range of hyperparameters**



Hypeparameter Optimization



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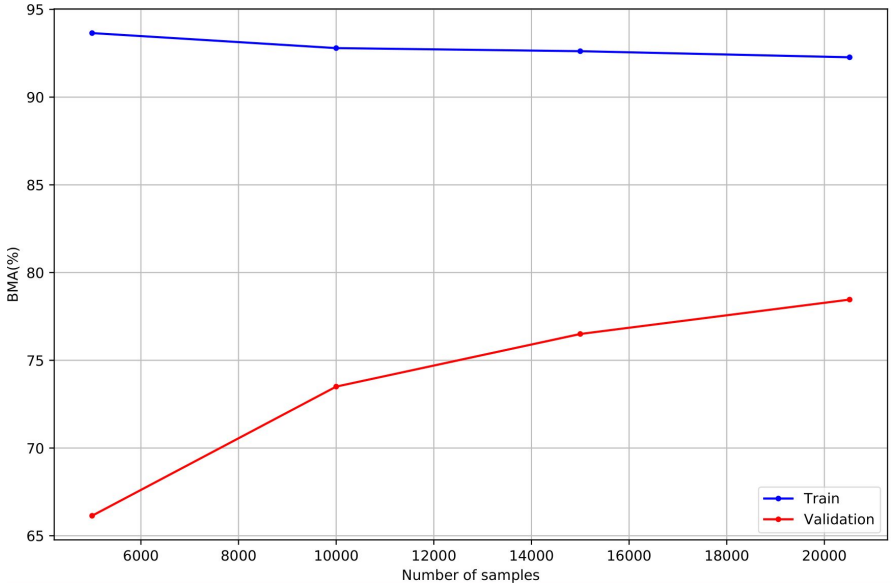
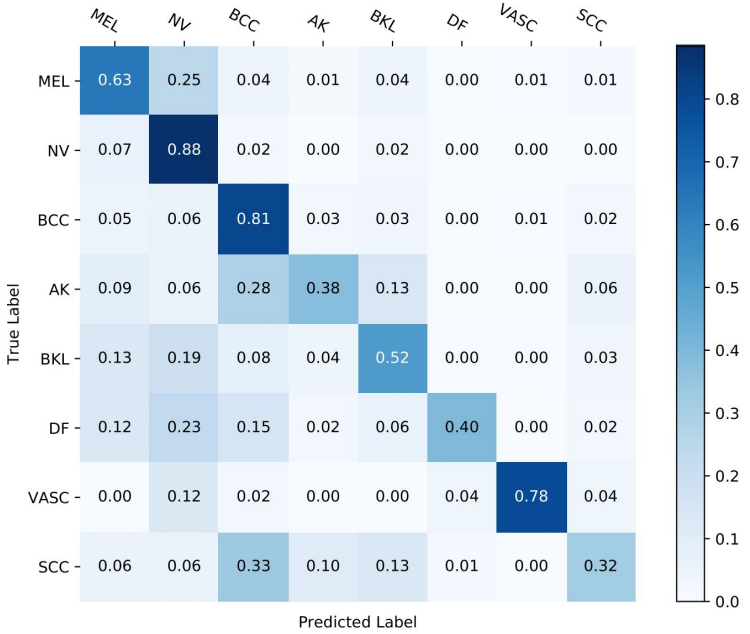
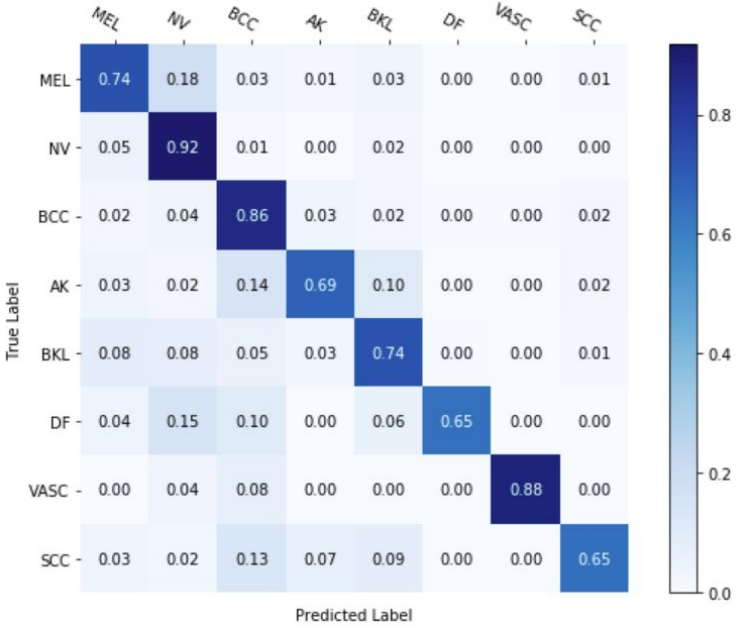
Impact of Dataset Size

- **Less overfitting**
- **Better generalization performance**
- More samples are needed to further reduce overfitting
- How to further increase performance?



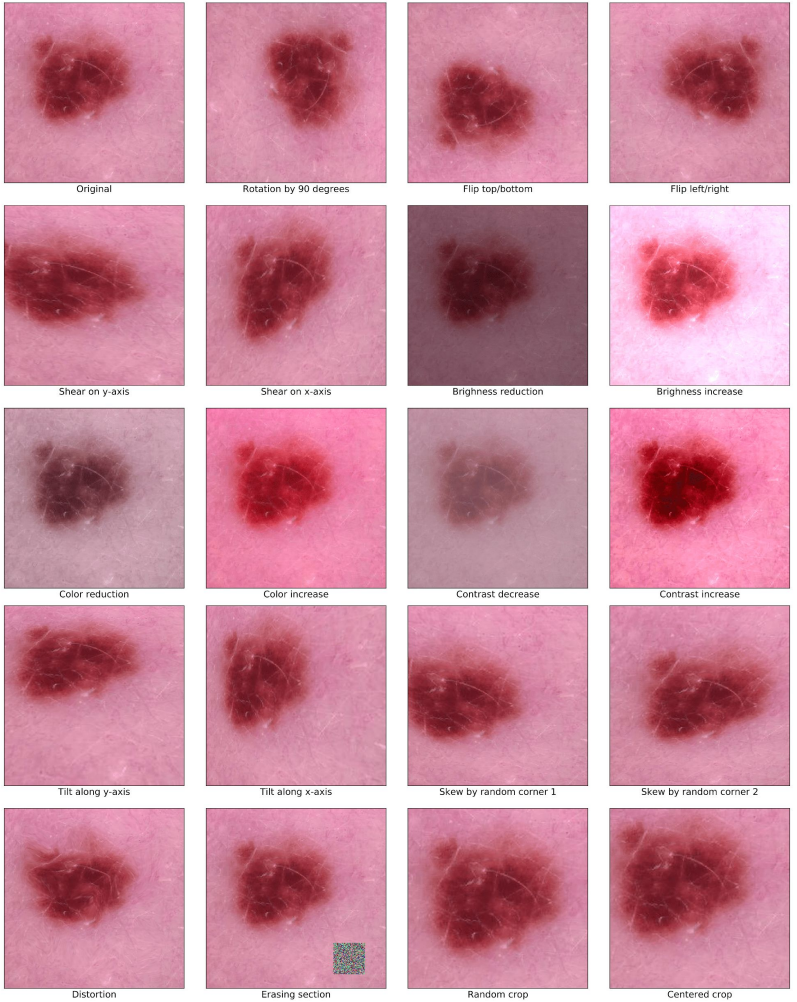
5000 samples vs 20518 samples





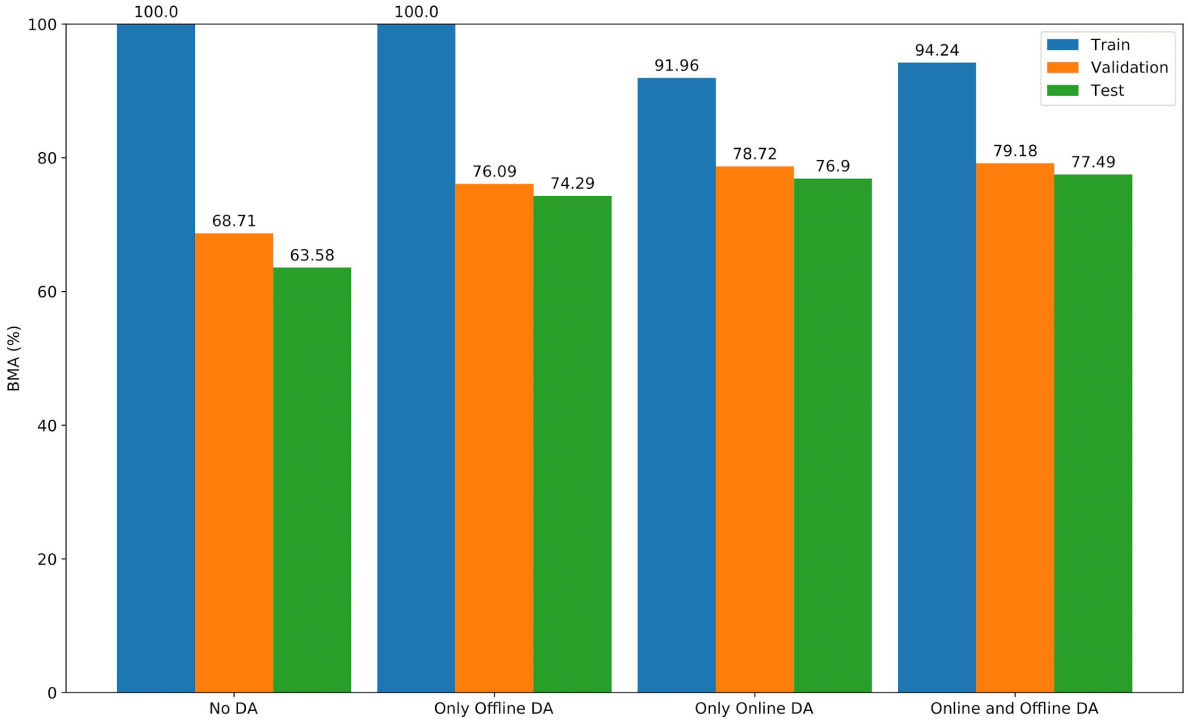
Data Augmentation Groups

- **Group 0:** No augmentation techniques
- **Group 1:** Slight variations to the original image;
- **Group 2:** Augmentation techniques of group 1 plus some adjustments on pixel intensities
- **Group 3:** Augmentation techniques of group 1 plus perspective transformations
- **Group 4:** Augmentation techniques of group 1 plus noise induction augmentation techniques



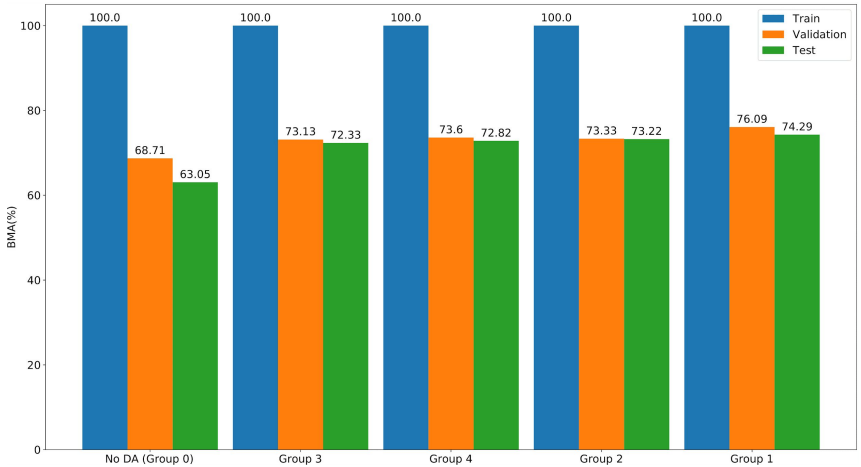
Offline vs Online Data Augmentation

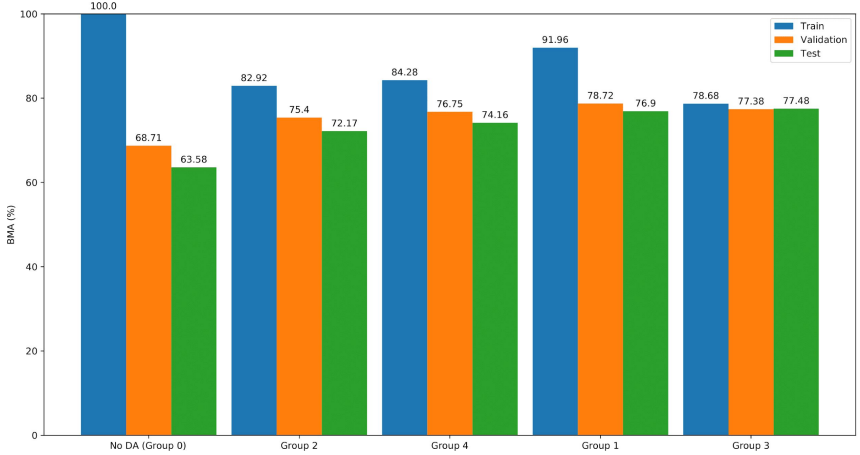
- **Offline** data augmentation used to **class balance** and **oversample** the dataset
- **Online** data augmentation used to **reduce overfitting** while training
- **Combining both reduces overfitting and improves generalization performance**



Augmentation Group Results

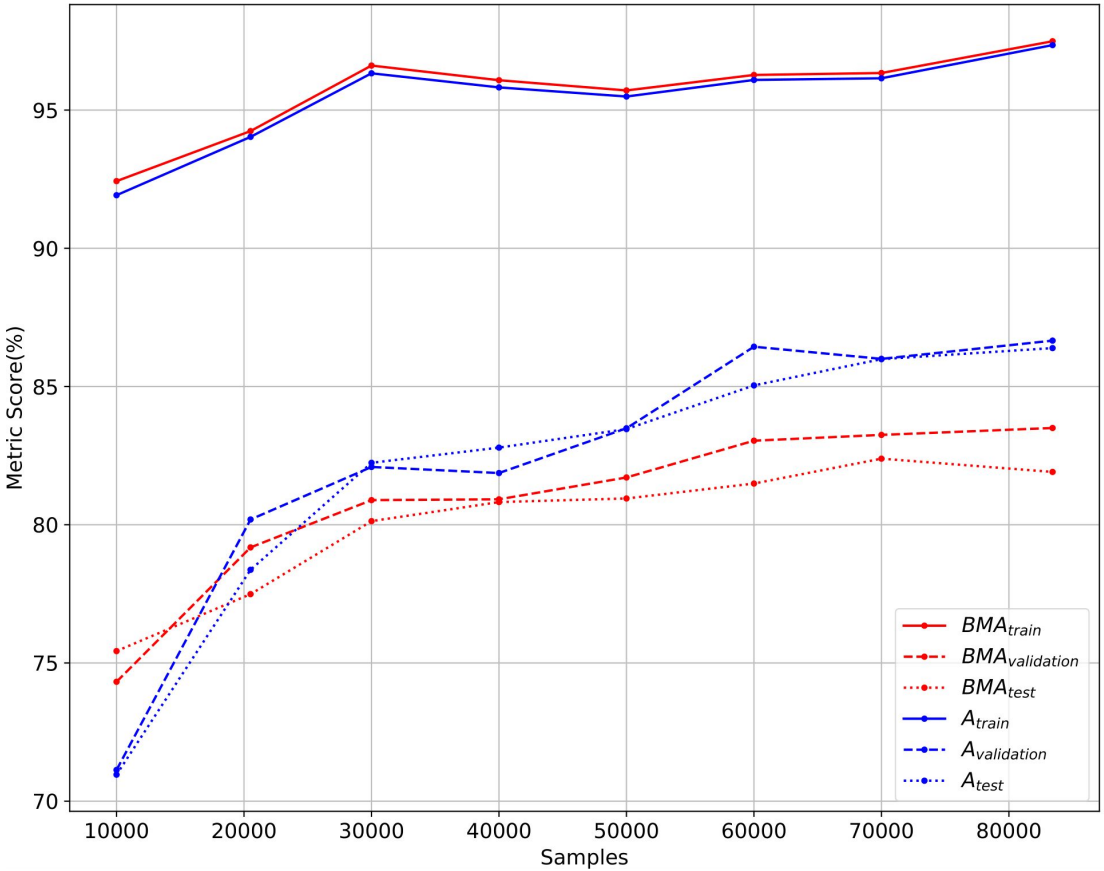
- **Offline:**
  - Complex augmentation remove important information
  - **Simpler augmentations perform better**
- **Online:**
  - Group 2 and 4 reduce overfitting but also reduce train, validation and test BMA
  - Group 3 dramatically reduces overfitting
  - Results are related to the way online data augmentation works
  - **Complex augmentations help generalize knowledge**



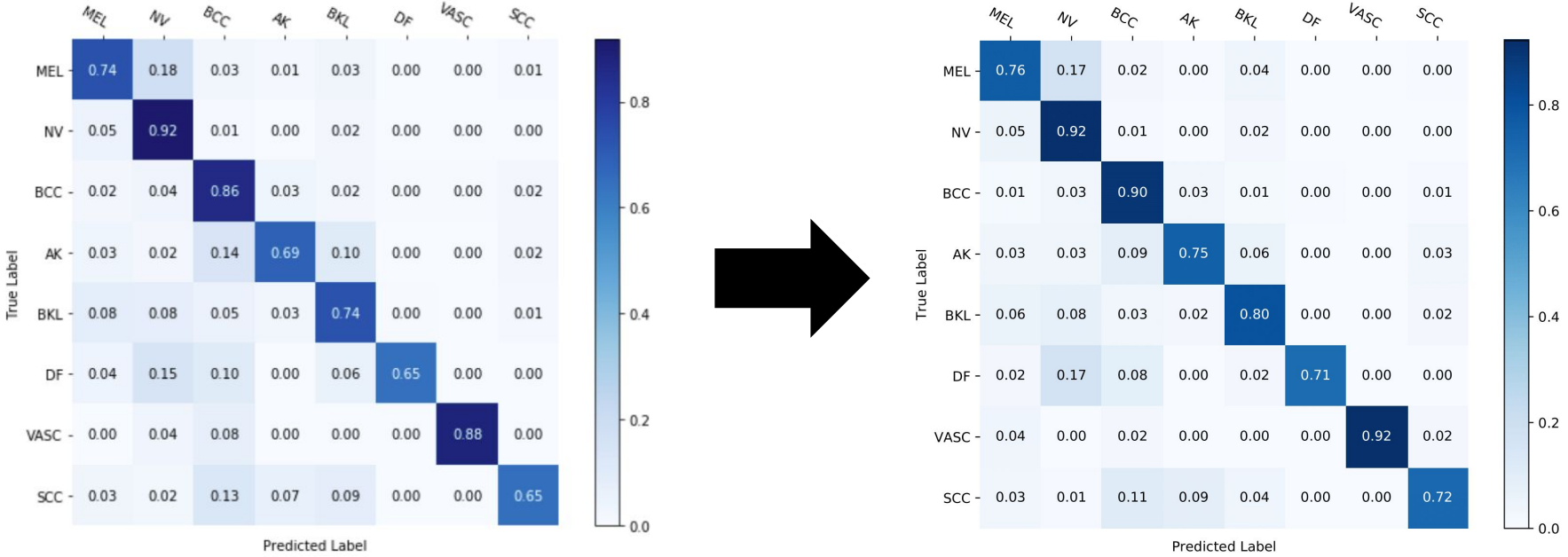


Class Balancing

- Oversampling through augmentation group 1
- **Performance increase on underrepresented classes**
- Gap between BMA and accuracy



Original Training Dataset (20518 samples) vs Synthetic Class-Balanced Dataset (83432 samples)



Ensemble

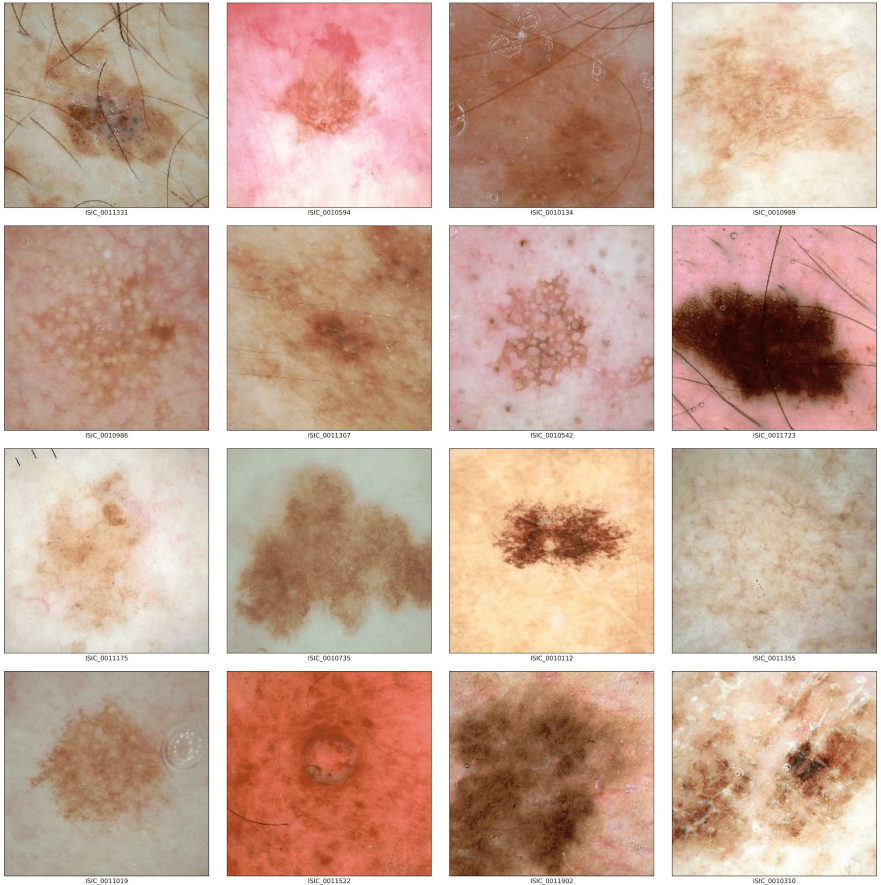
- Considerable improvement from single-model performance
- More models are not necessarily better
- **Very useful for benchmark challenges**

Approach Name	Pre-trained models	BMA	Accuracy
EfficientNetB2 approach	EfficientNetB2	≈ 0.820	≈ 0.851
DenseNet121 approach	DenseNet121	≈ 0.815	≈ 0.867
InceptionResNetV2 approach	InceptionResNetV2	≈ 0.811	≈ 0.862
ResNet152 approach	ResNet152	≈ 0.797	≈ 0.858
VGG16 approach	VGG16	≈ 0.753	≈ 0.824
Ensemble of best 2 models	EfficientNetB2, DenseNet121	≈ 0.842	≈ 0.878
Ensemble of best 3 models	EfficientNetB2, DenseNet121, InceptionResNetV2	≈ 0.846	≈ 0.891
Ensemble of best 4 models	EfficientNetB2, DenseNet121, InceptionResNetV2, ResNet152	≈ 0.841	≈ 0.894
Ensemble of all 5 models	EfficientNetB2, DenseNet121, InceptionResNetV2, ResNet152, VGG16	≈ 0.836	≈ 0.893

Single Model vs Ensemble of Best Three Models

Out of Training Distribution Samples

- Composed of different types of lesions from ISIC Archive, not belonging to the original distribution
- Same preliminary steps (i.e., pre-processing and split)



Out of training distribution detection

- Methods from the literature:
  - Top-1 softmax thresholding
  - Out-of-DIstribution detector for Neural networks (ODIN)
  - Outlier Class
- Outlier class outperforms other approaches
- Some limitations:
  - Low generalization performance:
    - Small set of samples
    - Clearly defined distribution
  - Bias in the training and test sets

Out-of-distribution method	BMA	Accuracy
Softmax threshold (0.7)	0.721	0.823
ODIN	0.654	0.691
Outlier class	0.750	0.847

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Results Discussion

- **Important methods to improve generalization performance:**
  - Transfer learning methodology + CNN pre-trained model
  - Dataset size
  - Data augmentation
- **Methods to consider:**
  - Hyperparameter tuning
  - Ensemble learning
  - Out-of-training distribution detection methods

Approach Step	BMA	Accuracy
Pre-trained model choice (see Section 5.1)	≈ 0.579	≈ 0.746
Hyperparameter tuned model (see Section 5.2)	≈ 0.585	≈ 0.754
Full dataset model without online DA (see Section 6.1.2)	≈ 0.636	≈ 0.799
Full dataset model with online DA (see Section 6.1.2)	≈ 0.769	≈ 0.849
Class balanced model (see Section 6.1.3)	≈ 0.815	≈ 0.867
Ensemble of 3 models (see Section 6.2)	≈ 0.846	≈ 0.891
Model with out-of-distribution detection (see Section 6.3)	≈ 0.750	≈ 0.847

Results Comparison

- **State of the art results on both single-model and multi-model performance for 8-class classification**
- 9-class classification tested with a different test set

Approach	In distribution (8 Classes)		Out of distribution (9 Classes)	
	BMA_{test}	A_{test}	BMA_{test}	A_{test}
3 Model Ensemble	0.846	0.891	0.775	0.858
DenseNet121	0.815	0.867	0.750	0.847
Gessert *et al.* (2019)	0.725	NA	0.636	NA
Zhou *et al.* (2019)	0.753	NA	0.607	NA
Hsin-Wei Wang (2019)	0.828	NA	0.505	NA

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Key Takeaways

- **Fine-tuning the convolutional base** is the optimal approach for skin lesion classification
- The choice of the **pre-trained model's architecture** can have a substantial impact
- Pre-trained models are well optimized for a wide range of **hyperparameters**
- The **augmentation techniques** used should be carefully selected
- **Online data augmentation** emerges as a method to reduce overfitting
- **Ensembling** multiple models is useful for benchmarks
- Re-training the model with an **outlier class** can become a viable approach as an **out of training distribution detection method**

Future Research

- Further research towards **online data augmentation**:
  - Explore other augmentation groups (*e.g.*, GANs)
  - Study the impact on other datasets (*e.g.*, ISIC 2020 challenge dataset)
- Lack of **interpretability/explainability** of deep learning models:
  - Hierarchical classifier
  - Display kernel filters during the inference phase
- Further research is required to integrate these models into the **clinical workflow**:
  - Get dermatology professionals involved
  - Focus on practicality rather than performance

Thank You