# A SkinCare projekt

Somfai Ellák, ELTE IK Mesterséges Intelligencia Tanszék





## Skincare Project 2020-2022

People:

- Ellák Somfai (TKP)
- András Lőrincz
- Marcell Pólik
- Benjamin Baffy (TDK)
- Ádám Szijártó (TDK)

Funding: - EIT Digital (2020) - TKP (as ELTE contribution)

- Partners:
  - Degetel (France)
  - Semmelweis University (Dept of Dermatology, Venereology and Dermatooncology)

Objectives:

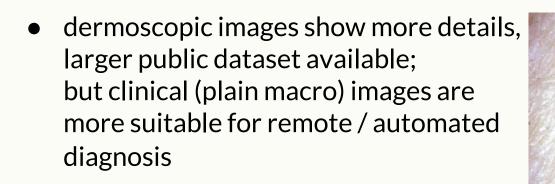
- industrial code for skin lesion classification

- related academic projects (next slides)



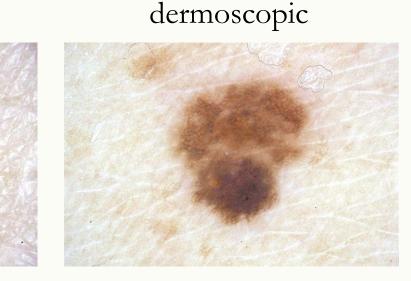
## **Challenges:**

 deadly melanoma images resemble benign naevus images, even human experts need extensive training





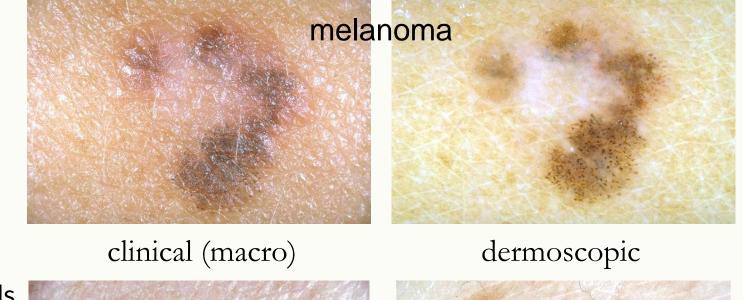
#### clinical (macro)

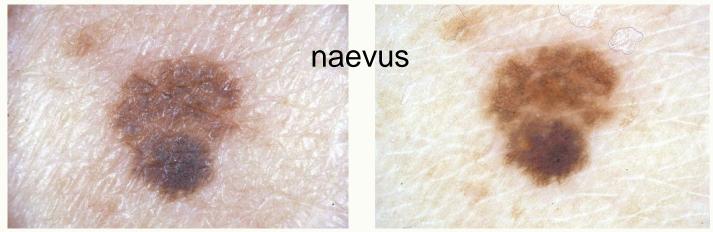




## **Challenges:**

- deadly melanoma images resemble benign naevus images, even human experts need extensive training
- dermoscopic images show more details, larger public dataset available; but clinical (plain macro) images are more suitable for remote / automated diagnosis

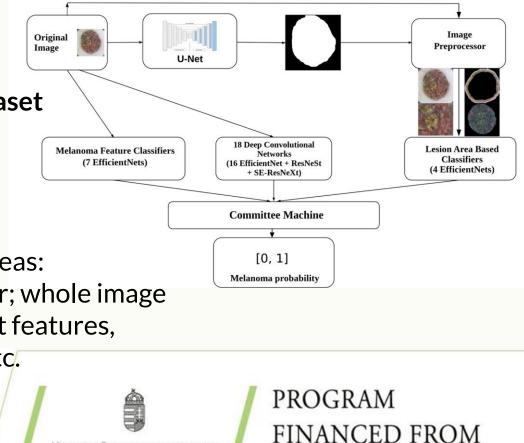






## Handling dataset dependence with model ensembles - skin lesion classification

- dataset dependence: a model trained on samples from clinic A performs better on *unseen* images from the same clinic than on images from clinic B even though both should sample the same distribution
- solution: (1) ensemble of heterogeneous models
  (2) trained on heterogeneous dataset
- our model ensemble: 29 deep CNNs
  - 18 models of 2020 champion (brute force)
  - 3+1 feature classifiers focused on key image areas: border, highlighted asymmetry, magnified center; whole image
  - 7 classifiers trained on dermatologically relevant features, such as blue-white veil, pigment network type etc.
  - model fusion: trained shallow NN



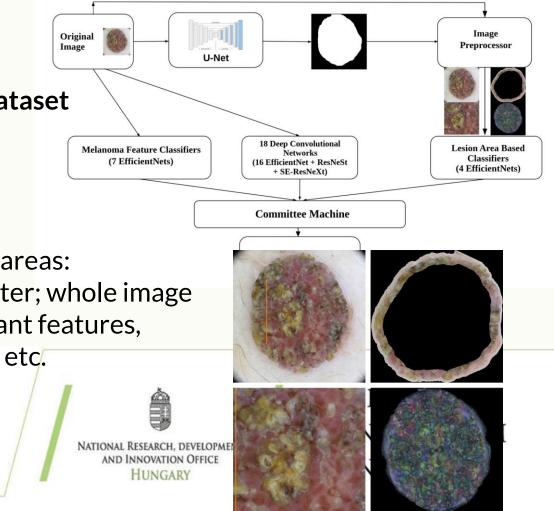
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## Handling dataset dependence with model ensembles - skin lesion classification

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## Handling dataset dependence with model ensembles - skin lesion classification

 performance: 93% balanced accuracy on training set (out-of-fold),
 84-91% on other datasets

Balanced accuracy (%)	predict of	n out-of-fold	predict on other dataset		
	C-ISIC	DERM7D	DERM7D	PH2	Semmelweis
AVG-18	89.12		79.2	84.1	77.0
Calib.Prob.AVG-18	93.45		82.5	91.9	81.8
Committee-18	93.44		83.6	90.9	83.2
Committee-22	93.56		84.8	90.9	83.1
Committee-29	93.51	84.8	(	91.2	83.6
estimated error	±0.04	$\pm 0.2$	$\pm 0.2$	$\pm 0.3$	$\pm 0.4$

- the ensemble can be re-trained for clinical (macro) images less image details, smaller public datasets transfer learning for deepnets, for committee machine, or both?
  - naive approach (blue  $\leftarrow$ ) yields poor results: fine-tuning dataset too small
  - best solution (red): use adaptive sharpness aware minimization with fine-tuning

transf. learning	committee	DERM7M	PAD-UFES	MED-NODE	Average over	
in deepnets	machine	(train+test)	(test)	(test)	3 datasets	
no	plain	70.2±1.1	$71.6 \pm 0.7$	<b>89.4</b> ±0.9	77.1±0.5	
no	SAM	<b>69.7</b> ±1.2	$71.2 \pm 1.1$	<b>89.4</b> ±1.1	<b>76.8</b> ±0.7	
plain	plain	<b>72.0</b> ±0.6	$69.2 \pm 1.0$	$81.4 \pm 1.1$	74.2±0.5 ←	
plain	ASAM	$73.2{\pm}0.6$	$73.1 \pm 1.1$	$87.5 \pm 1.3$	<b>77.9</b> ±0.6	PROGRAM
ASAM	plain	74.4±1.5	$72.4{\pm}0.4$	$86.6 \pm 1.2$	$77.8 \pm 0.7$	
ASAM	ASAM	<b>74.9</b> ±1.1	<b>74.1</b> ±0.5	$88.7 \pm 1.0$	<b>79.2</b> ±0.5	FINANCED FROM
		1			HUNGARY	THE NRDI FUND

manuscript submitted, under peer review

## Thickness prediction of melanoma lesions

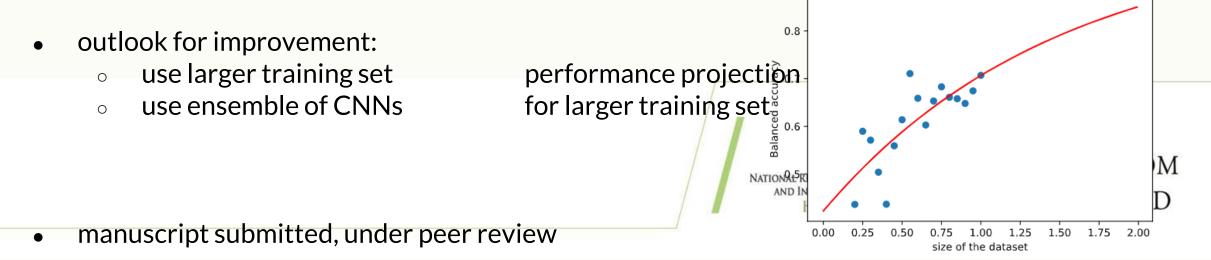
- lesion thickness: proxy for tumor progression application: prioritizing the most urgent cases for treatment
- used single CNN to compare with literature results important: (1) reduce the effects of sample imbalance, (2) proper augmentation
- achieved 71% balanced accuracy for 3-way classification (3 discreet thickness classes) better than literature results Except one (Jaworek-Korjakowska et al. 2019): claimed 87% accuracy BUT: we discovered they made a mistake at data preparation, causing data leak to test set (reproduced their work). After fixing data leak: only 68% accuracy
- outlook for improvement:
  - use larger training set
  - use ensemble of CNNs

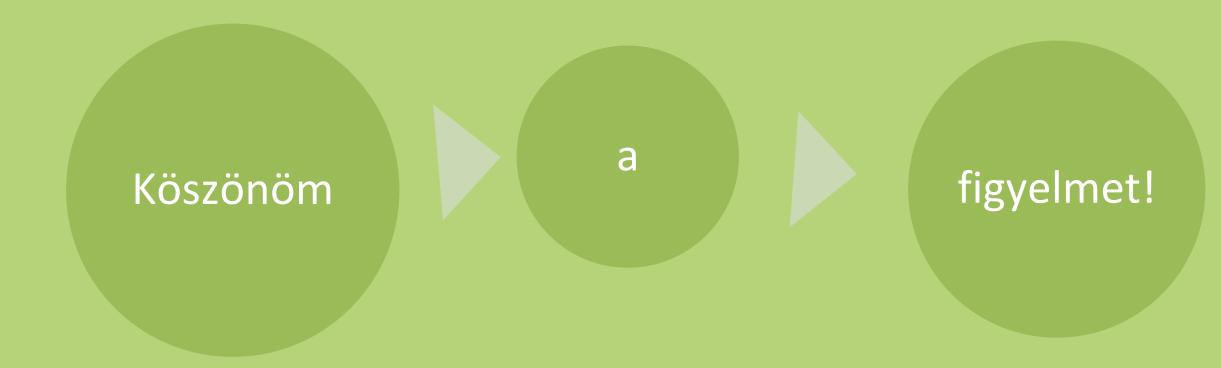


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## **Thickness prediction of melanoma lesions**

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