

Machine Learning in Dermatology: 2D Images, 3D Scans, and Regional Applications and Integrations

Jeremy Kawahara, PhD



AIP LABS®



Background

PhD in Computing Science at Simon Fraser University, Canada

- Medical Image Analysis Lab @ SFU

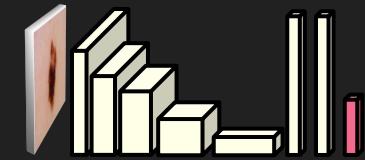


SIMON FRASER
UNIVERSITY



Publishing works on deep learning for dermatology since 2016

Working in industry developing a dermatology application used in Europe



Outline



Prior research

- 2D dermatology images
- Two works on full body 3D scans

Current work

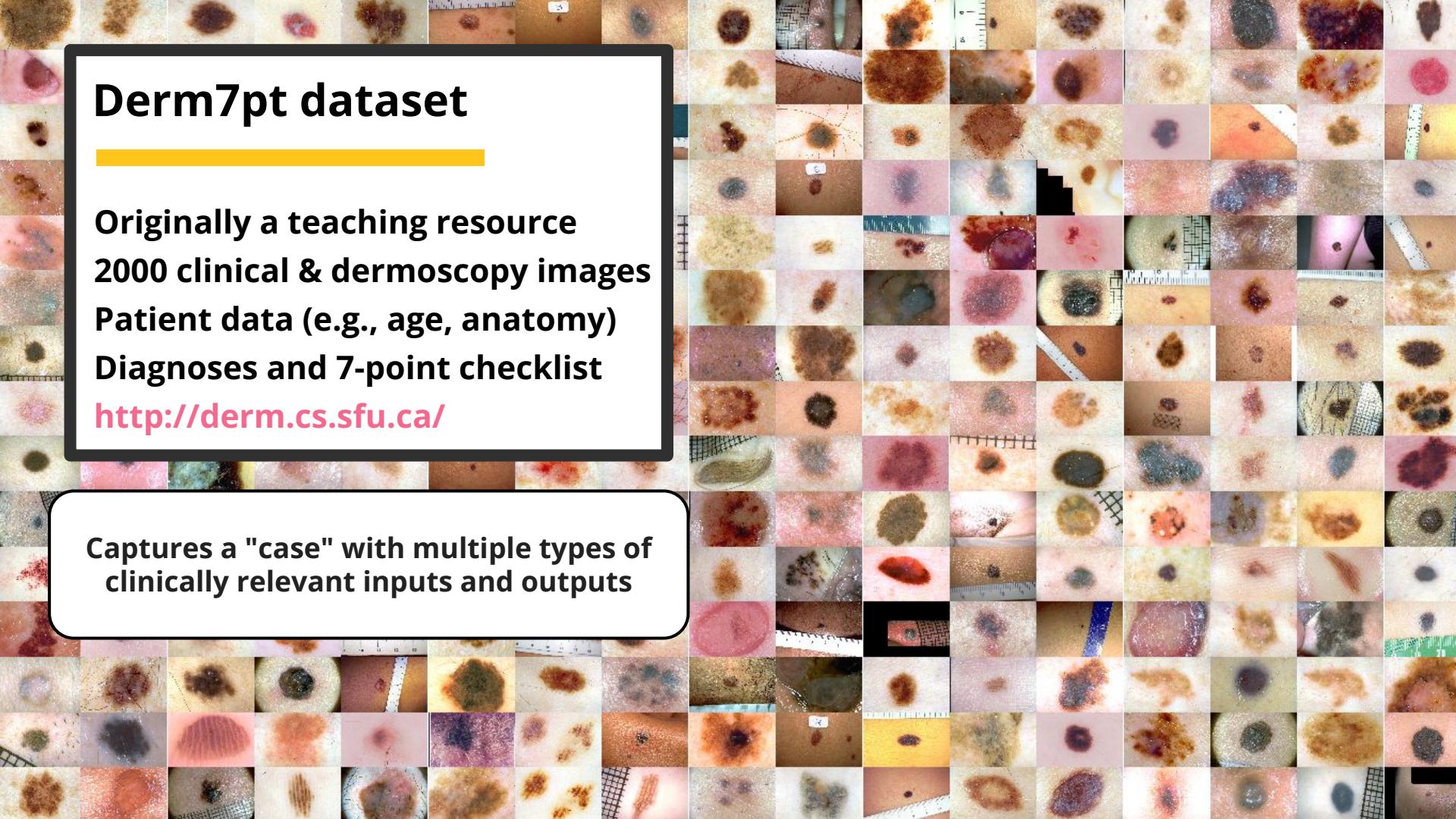
- Dermatology application in Europe



Derm7pt dataset

Originally a teaching resource
2000 clinical & dermoscopy images
Patient data (e.g., age, anatomy)
Diagnoses and 7-point checklist
<http://derm.cs.sfu.ca/>

Captures a "case" with multiple types of clinically relevant inputs and outputs



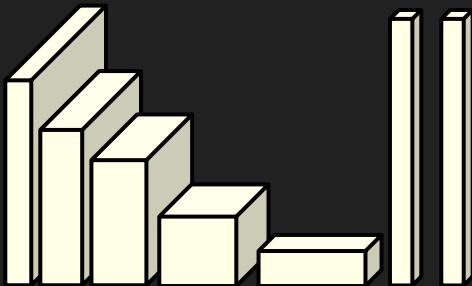
7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Corresponding paper with data

Architecture designed with this data in mind

Dermoscopy



Diagnoses



Melanoma

Seborrheic Keratosis

Basal Cell Carcinoma

Nevi

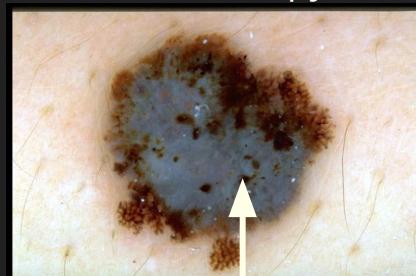
Start with a standard CNN to predict the diagnosis from the image

Extend architecture to handle multiple types of inputs and outputs

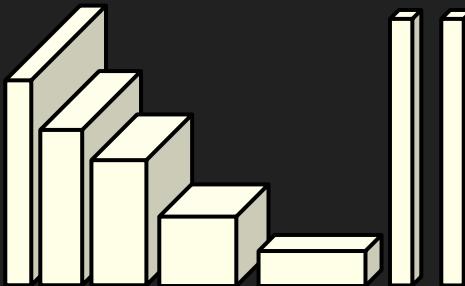
7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

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Dermoscopy



"Present" suggests melanoma



Diagnoses



Melanoma

Seborrheic Keratosis
Basal Cell Carcinoma

Nevi

Other types of relevant outputs

"Irregular" suggests melanoma

Blue Whitish Veil



Absent
Present

Pigmentation



Absent
Irregular
Regular

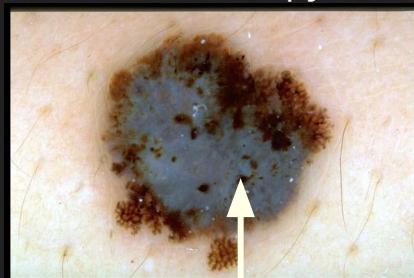
7-point contains checklist items that are related to melanoma

Showing 2 of the 7 checklist items

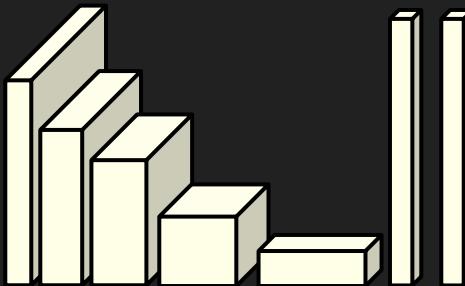
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Dermoscopy



"Present" suggests melanoma



Diagnoses



Melanoma

Seborrheic Keratosis

Basal Cell Carcinoma

Nevi

Multi-task problem: Each task with own loss



Blue Whitish Veil



Absent

Present

Pigmentation



Absent

Irregular

Regular

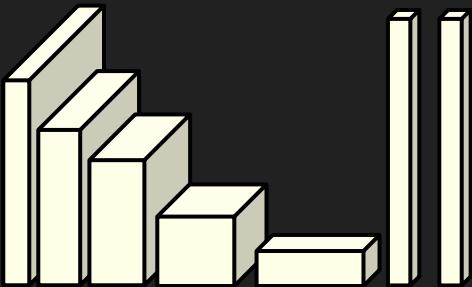
Represent multiple losses with L

"Irregular" suggests melanoma

7-Point Checklist and Skin Lesion Classification using Multi-Task **Multi-Modal** Neural Nets

Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Dermoscopy



Predictions should be a function of all the input data

Patient age, sex, anatomy

Clinical/Macroscopic



Other types of inputs

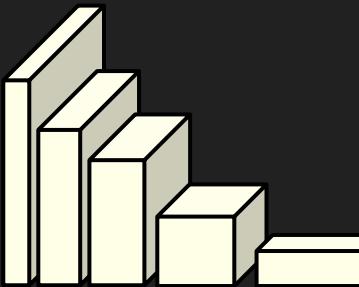
L

7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Extend architecture to jointly train and learn relationships across all inputs

Dermoscopy

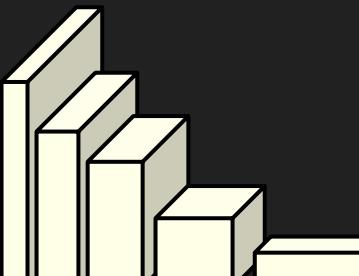


Smaller CNNs for each modality

Final network uses all input features

Patient age, sex, anatomy

Clinical/Macroscopic



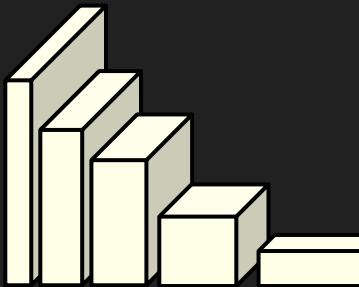
Single model and single optimization

7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

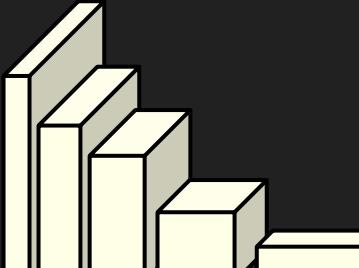
Predictions using patient info, dermoscopy, and clinical images

Dermoscopy



Patient age, sex, anatomy

Clinical/Macroscopic



$$L_{dcm}$$

73.4

Averaged accuracy

7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

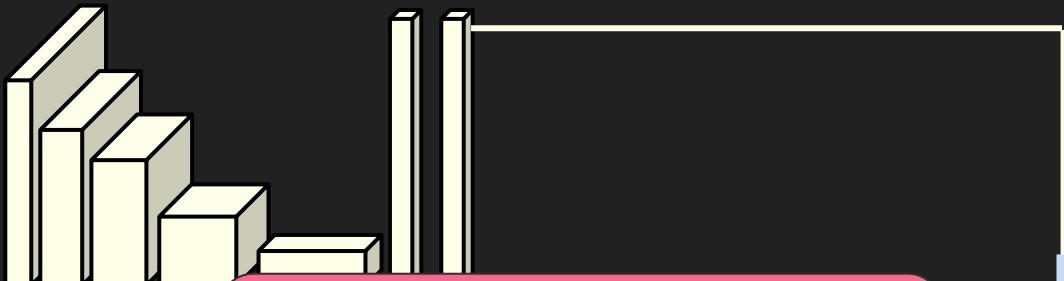
Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Dermoscopy



Patient age, sex, anatomy 

Clinical/Macroscopic



How to handle missing modalities at test time?

$$L_{dcm}$$

73.4

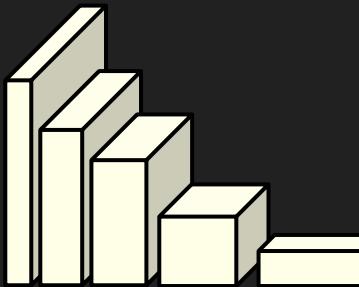


7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

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Add dermatoscopy only loss

Dermoscopy



Patient age, sex, anatomy 

Clinical/Macrosopic



Loss does not need
other types of input

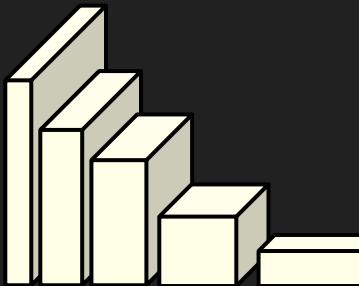
Averaged
accuracy



7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

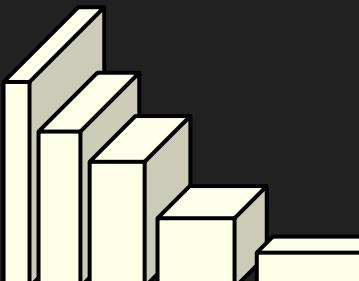
Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Dermoscopy



Patient age, sex, anatomy

Clinical/Macroscopic



Degrades due to
7-point



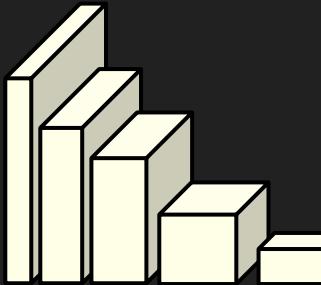
Averaged
accuracy

7-Point Checklist and Skin Lesion Classification using Multi-Task Multi-Modal Neural Nets

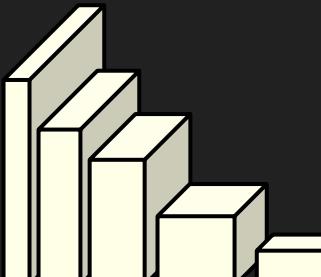
Jeremy Kawahara, Sara Daneshvar, Giuseppe Argenziano, Ghassan Hamarneh

Using all input data yields highest performance

Dermoscopy



Patient age, sex, anatomy



72.5

72.9

65.3

64.1

Averaged accuracy

73.4

From 2D to 3D skin image analysis

Clinical/macrosopic



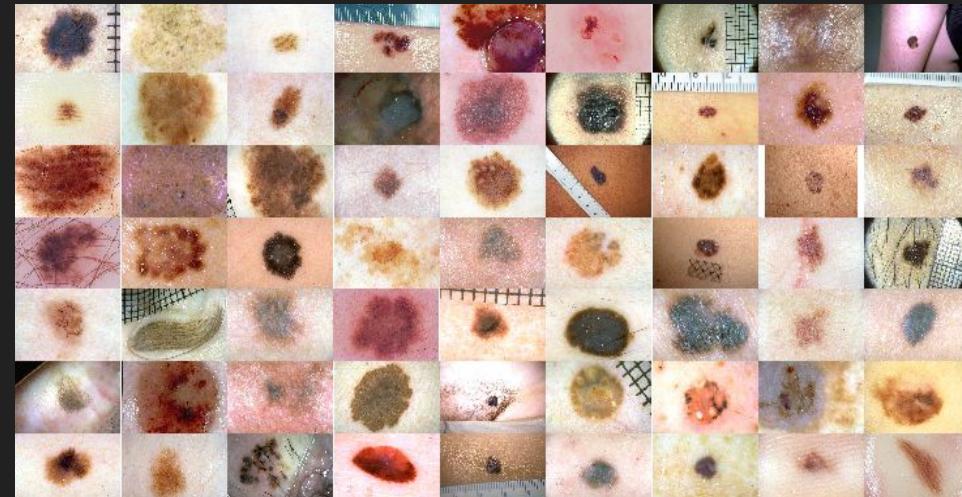
Dermatoscope



Canfield VECTRA WB360



Derm7pt: 2D clinical and dermoscopy images



3D scans of the
human body



3DBodyTex

3DBodyTex: Textured 3D Body Dataset

SAINT, Alexandre Fabian A  ; AHMED, Eman  ; SHABAYEK, Abd El Rahman  et al.

2018 • In 2018 Sixth International Conference on 3D Vision (3DV 2018)

200 subjects: 100 males and 100 females in two poses each



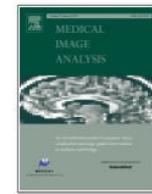
<https://cv2.uni.lu/3dbodytexv1/>



Medical Image Analysis

Available online 30 December 2021, 102329

In Press, Journal Pre-proof [?](#)



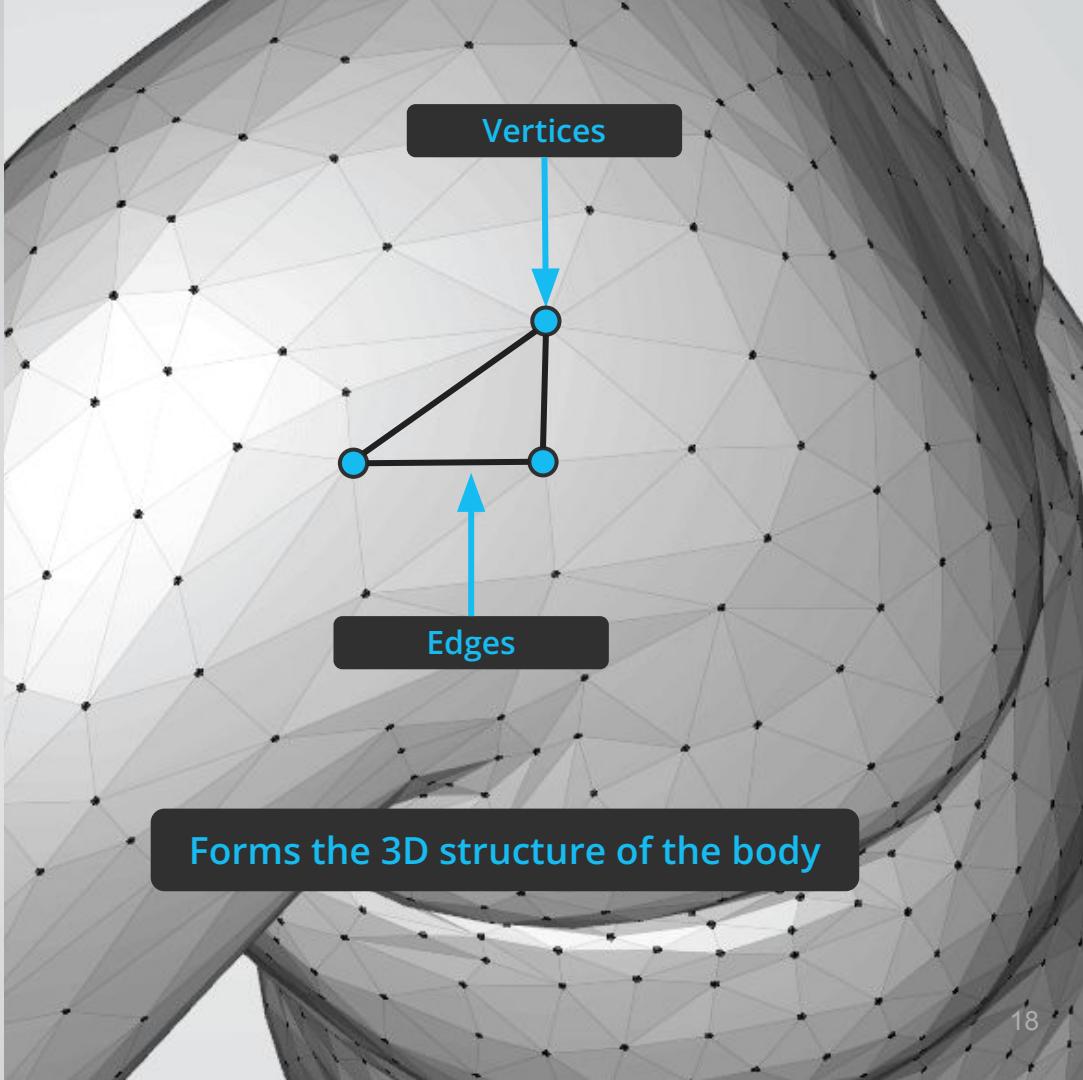
Skin3D: Detection and Longitudinal Tracking of Pigmented Skin Lesions in 3D Total-Body Textured Meshes

Mengliu Zhao ^{1, a}, Jeremy Kawahara ^{1, a}, Kumar Abhishek ^a, Sajjad

Shamanian ^a, Ghassan Hamarneh ^{2, a}✉

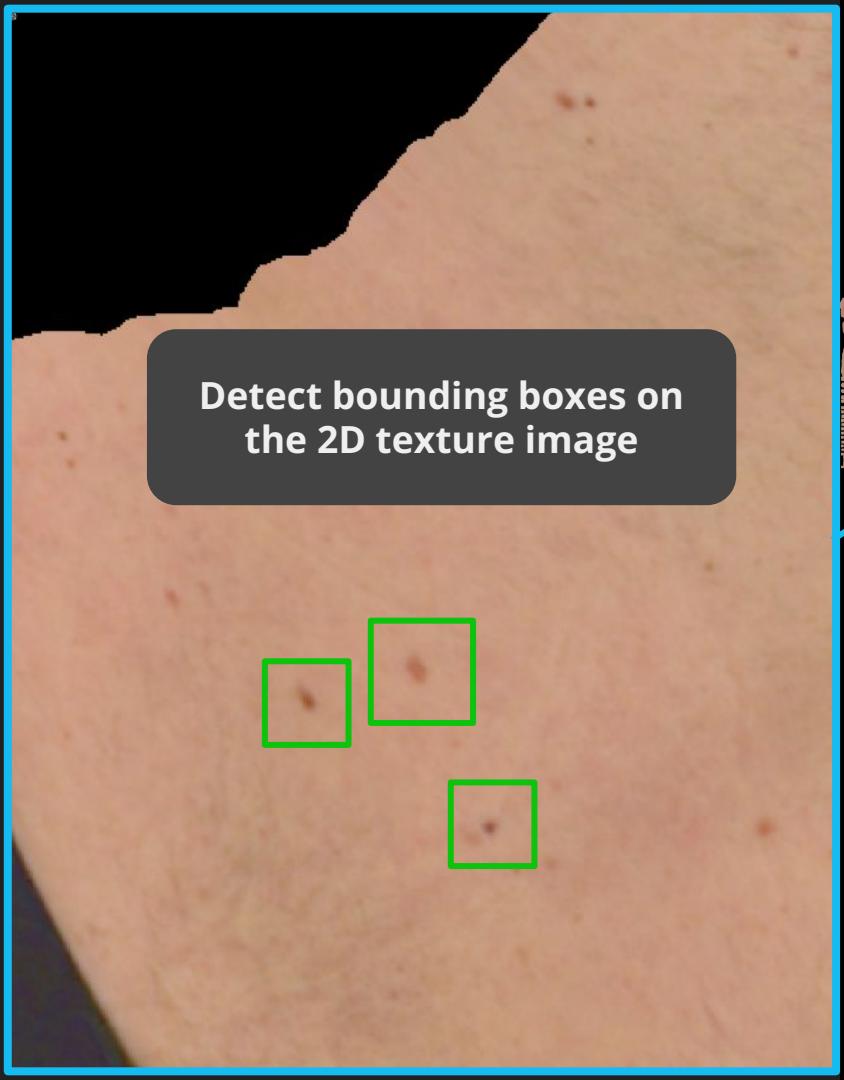
**Goal: Place a bounding box around
moles on the 3D body**



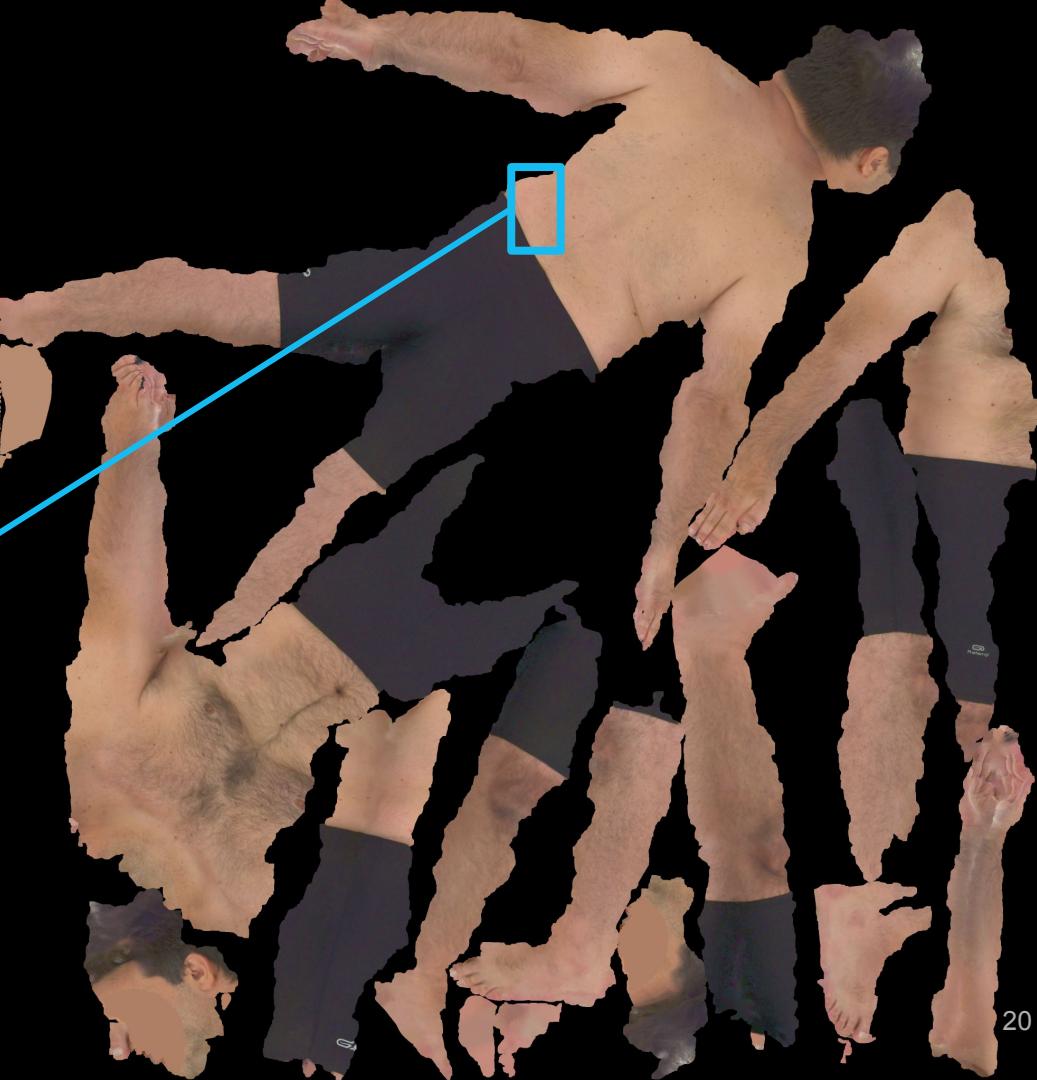


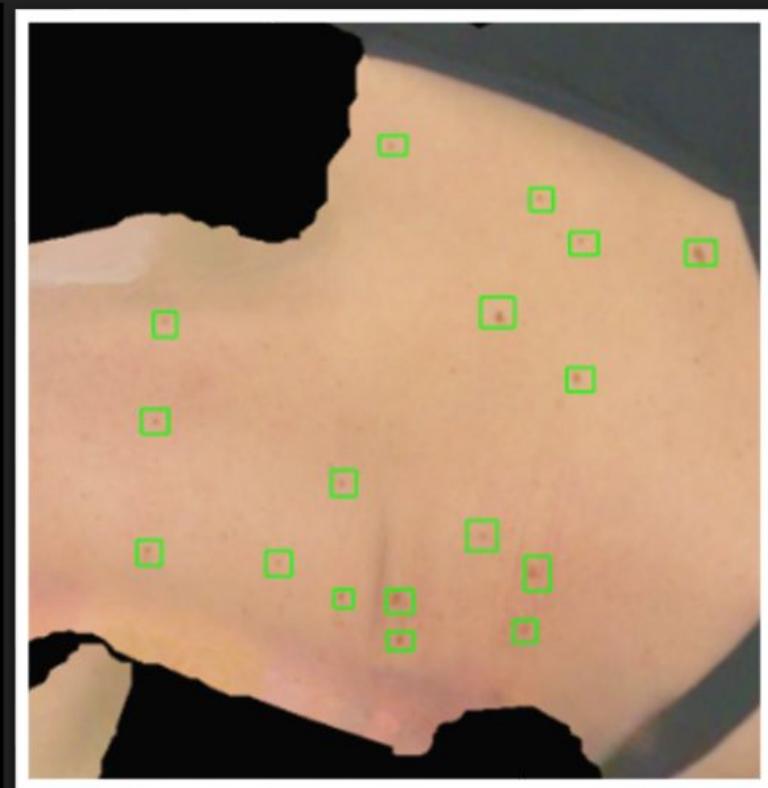


2D texture image maps to the 3D body



Detect bounding boxes on
the 2D texture image





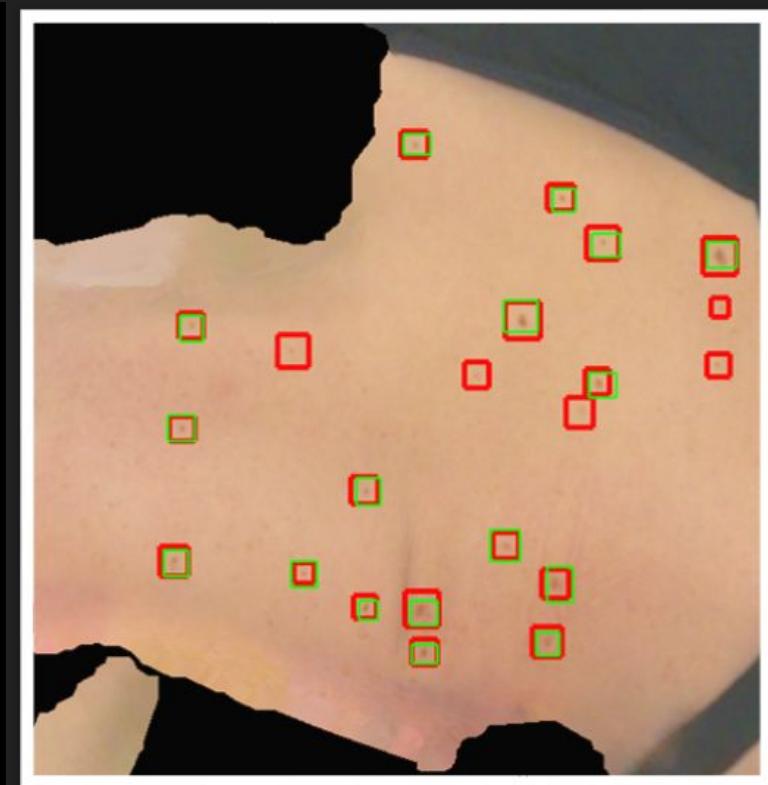
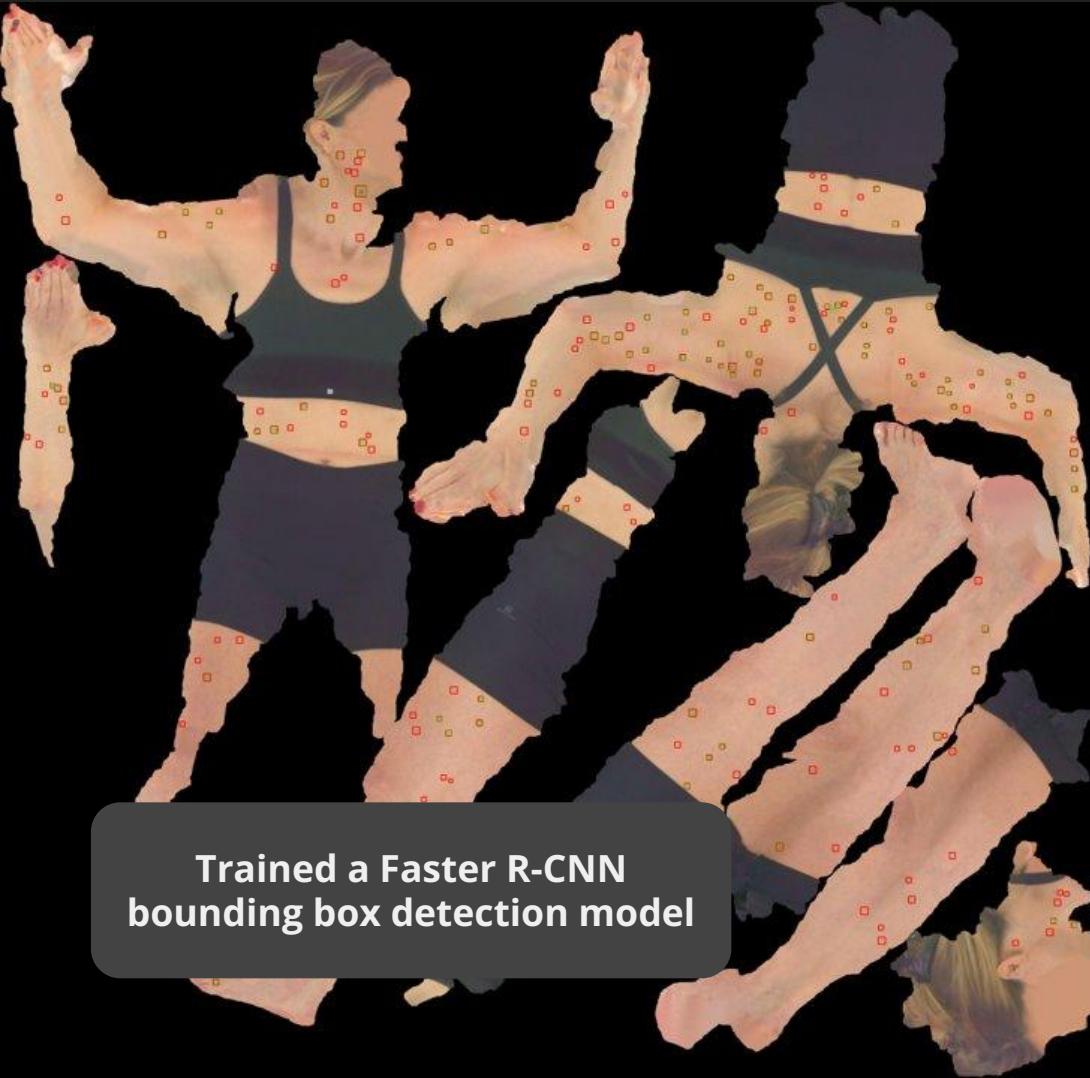
Require annotated data

Manually annotated

~25,000 bounding boxes

<https://www.robots.ox.ac.uk/~vgg/software/via/>

V G G
I M A G E
A N N O T A T O R



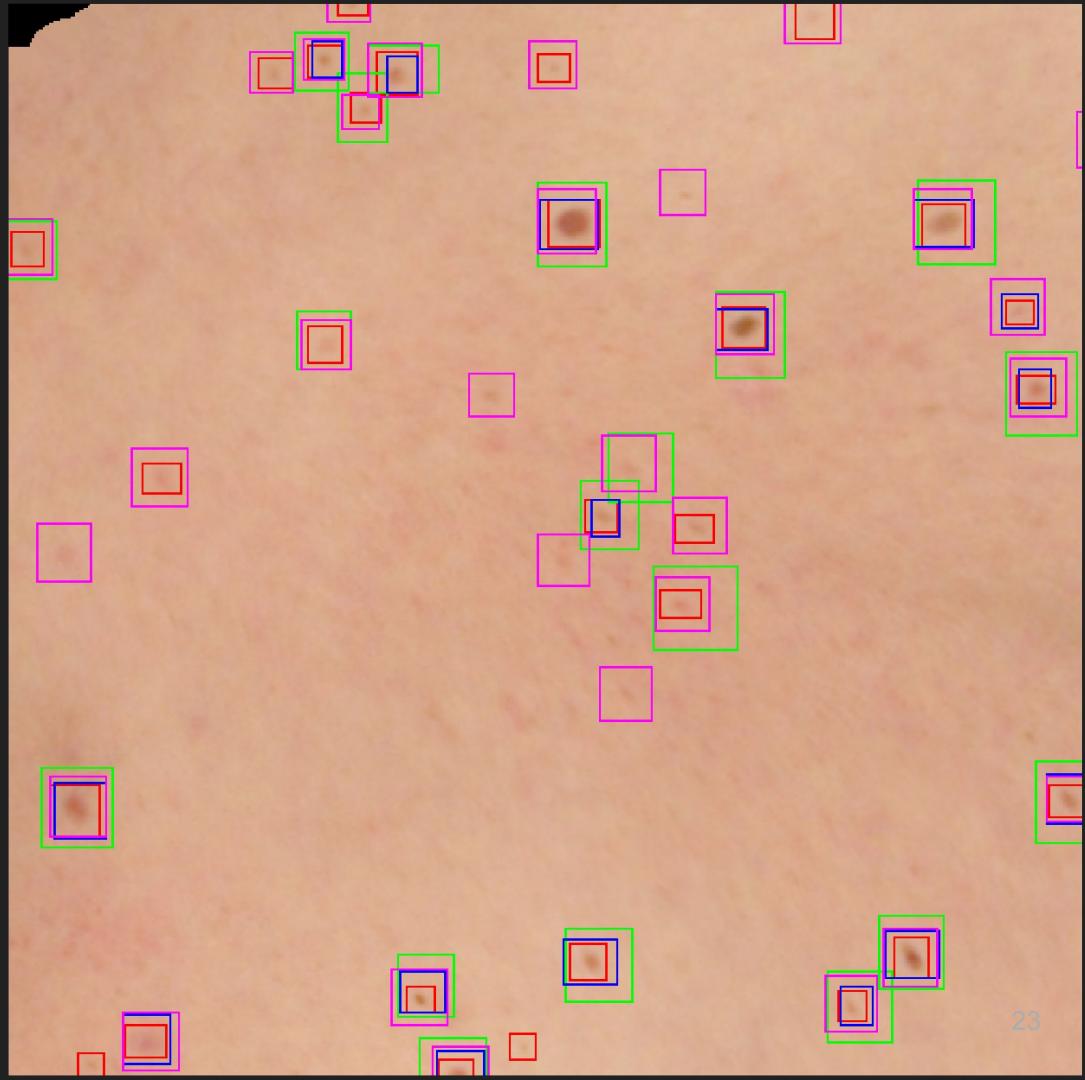
Evaluations

Machine predictions compared
with a single human annotator

Recall	Precision
0.84	0.66

Inter-annotator performance

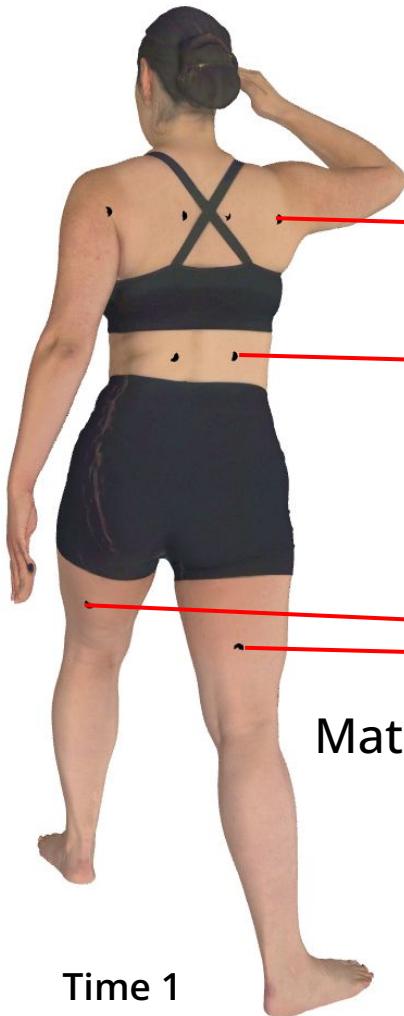
2 out of 3 human annotators agreed
more with the **machine** annotations
than any other human



Map the 2D detected lesions
back to the 3D body



Same subject in 2 poses



Time 1



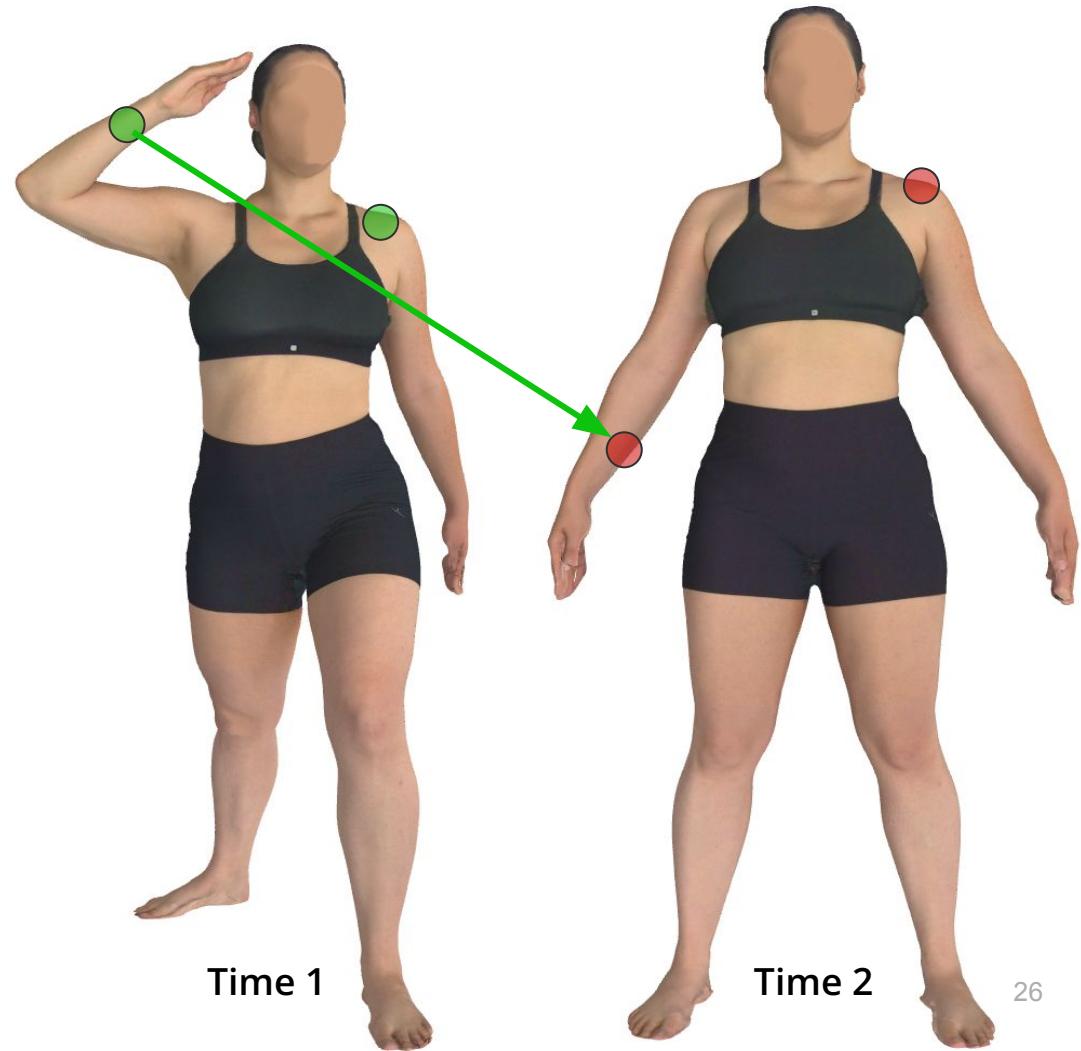
Time 2

Match corresponding lesions

Matching Lesions

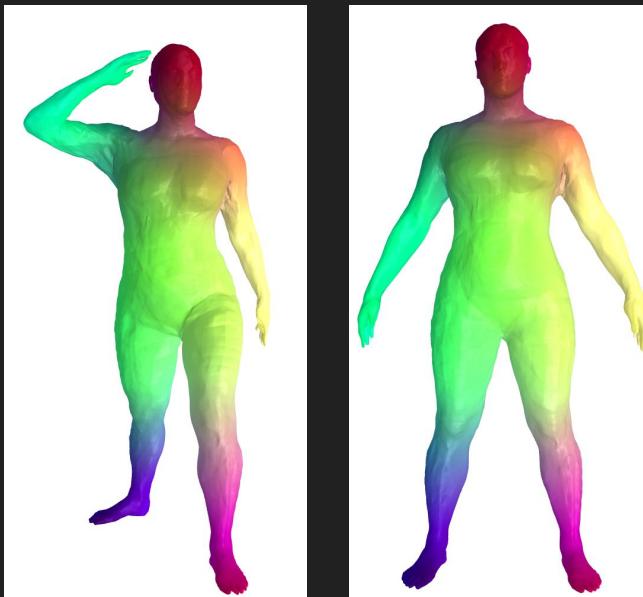
Same subject, two scans

Two lesions we want to track
across scans

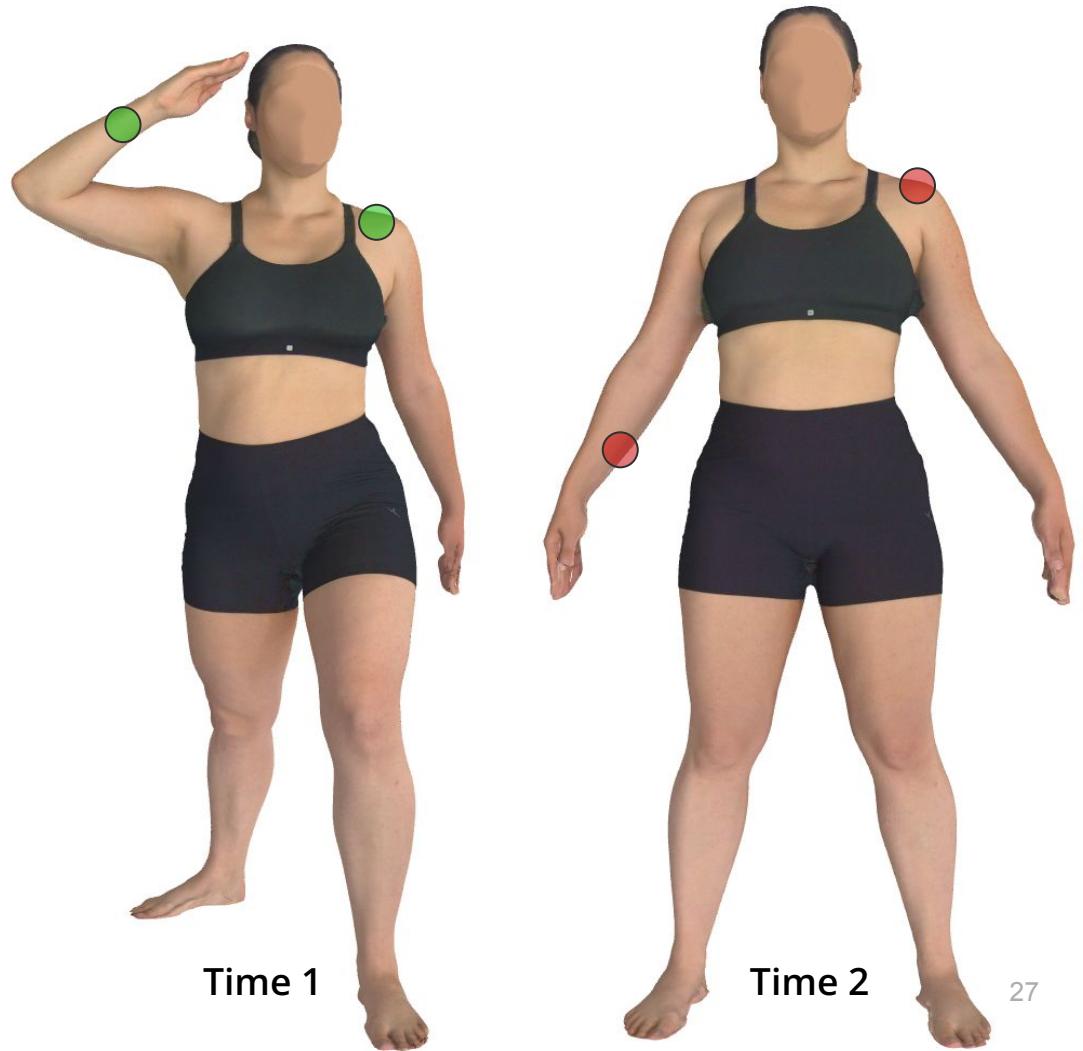


Matching Lesions

3D vertex correspondence
using a common template



3D-CODED: 3D Correspondences by Deep Deformation. Groueix et. al., ECCV, 2018.



Time 1

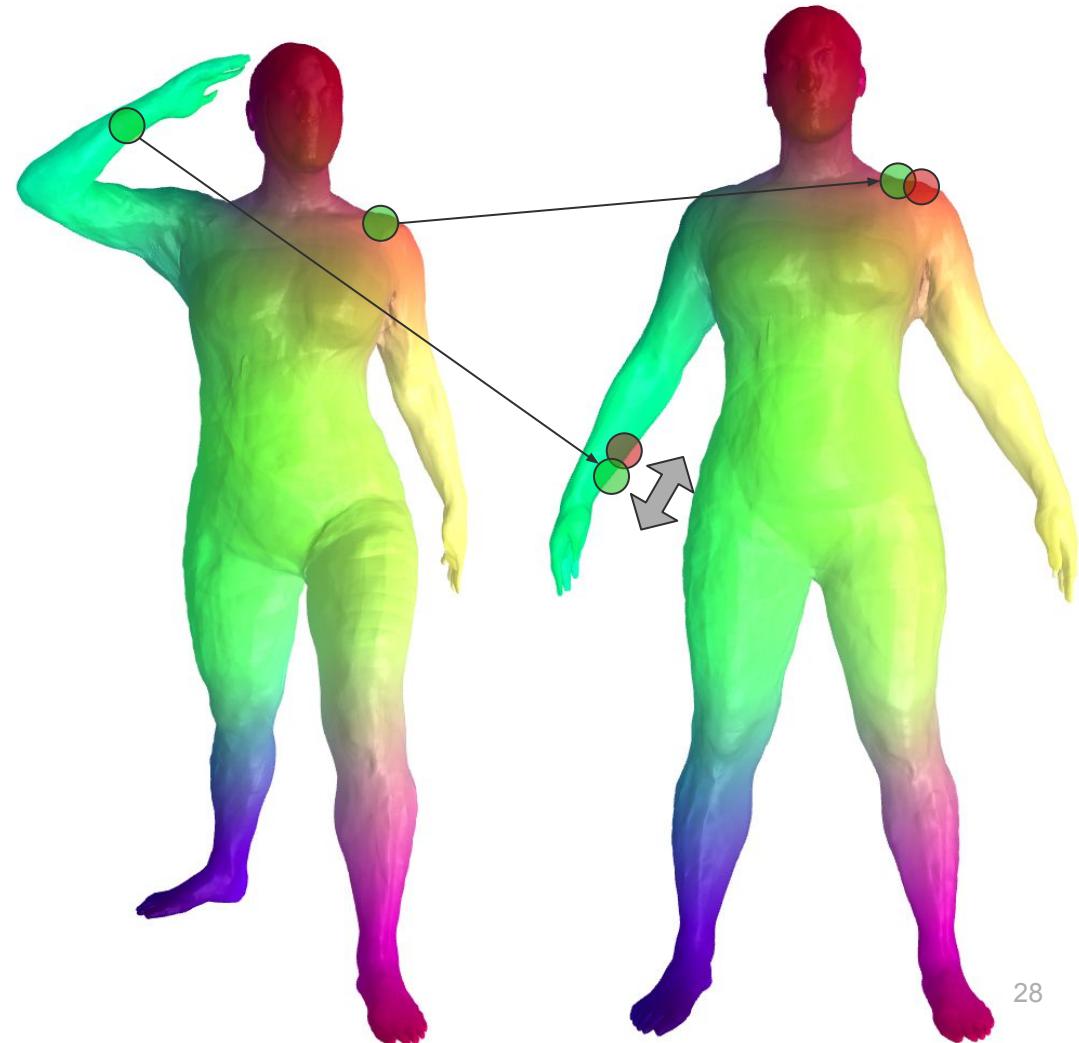
Time 2

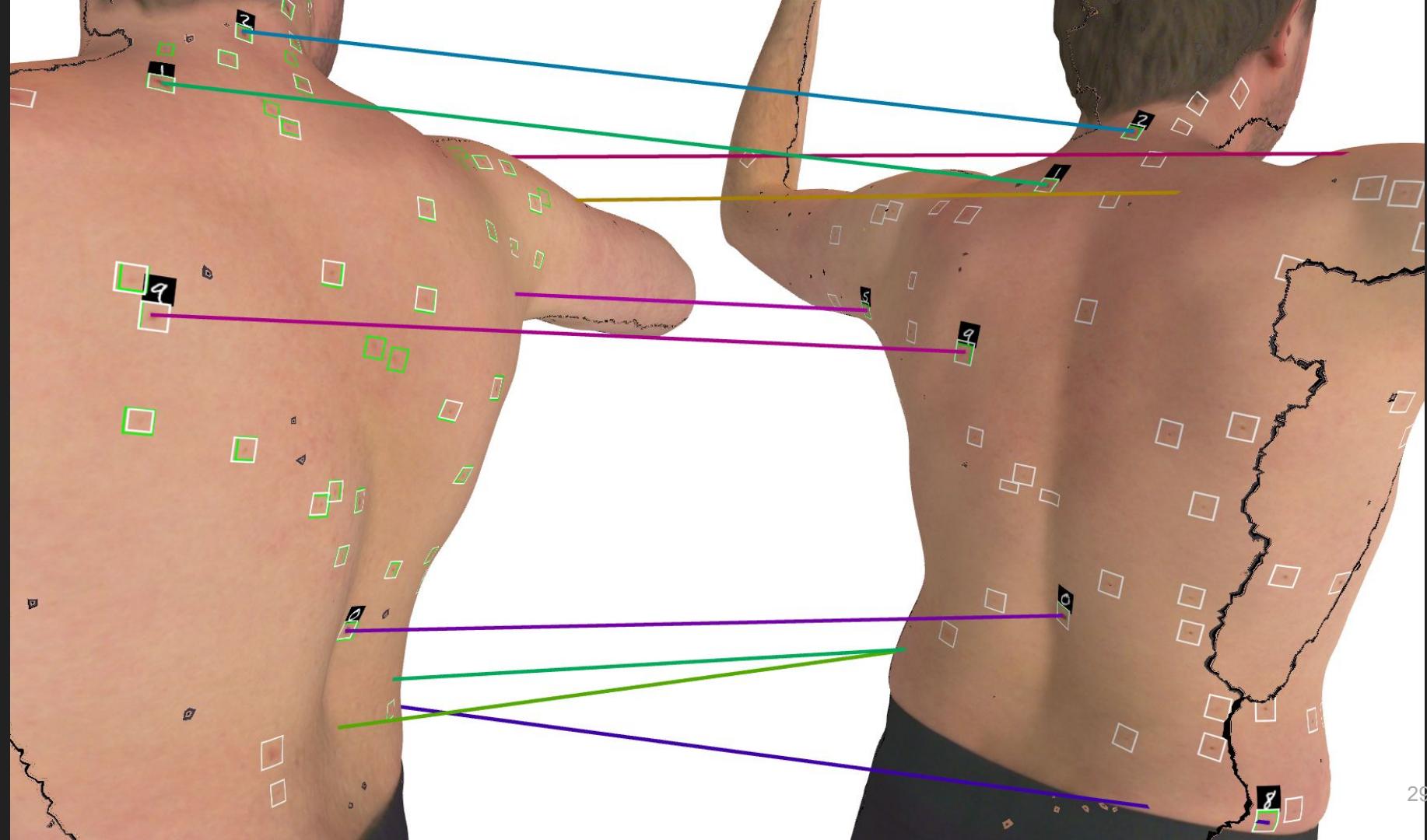
Matching Lesions

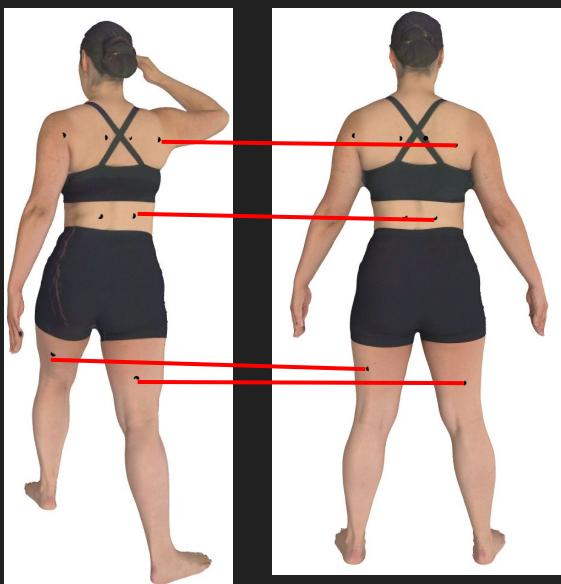
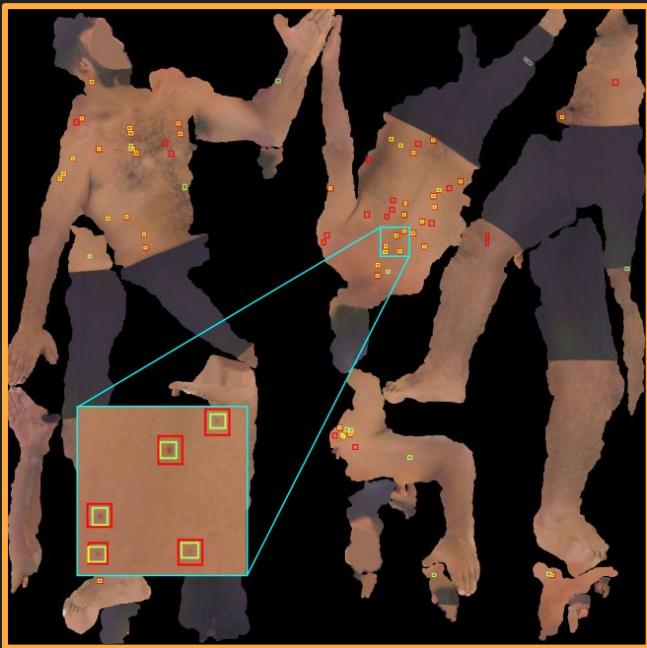
Map lesion to corresponding vertex on other scan

Compare the geodesic distance between lesions on the same mesh

Closer mapped lesions indicate the same lesion







Skin3D: bounding boxes on 3D meshes

<https://github.com/jeremykawahara/skin3d>

- **25,000** bounding boxes
- **200** subjects from 3DBodyTex
- Matched a subset of lesions across scans



DermSynth3D: Synthesis of in-the-wild annotated dermatology images

Ashish Sinha ^{a,1}, Jeremy Kawahara ^{a,1}, Arezou Pakzad ^{a,1}, Kumar Abhishek ^a,
Matthieu Ruthven ^b, Enjie Ghorbel ^{b,c}, Anis Kacem ^b, Djamil Aouada ^b,
Ghassan Hamarneh ^a

Real lesion on 2D image



3D body scan



2D lesion transferred to 3D body



Maintain lesion appearance while
blending well on the 3D body

2D view



2D annotations



Potential application:
Synthesize 2D image datasets
for machine learning tasks

DermSynth3D: Synthesis of in-the-wild annotated dermatology images

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Matthieu Ruthven ^b, Enjie Ghorbel ^{b c}, Anis Kacem ^b, Djamilia Aouada ^b,
Ghassan Hamarneh ^a  

3D body scan



2D lesion transferred to 3D body

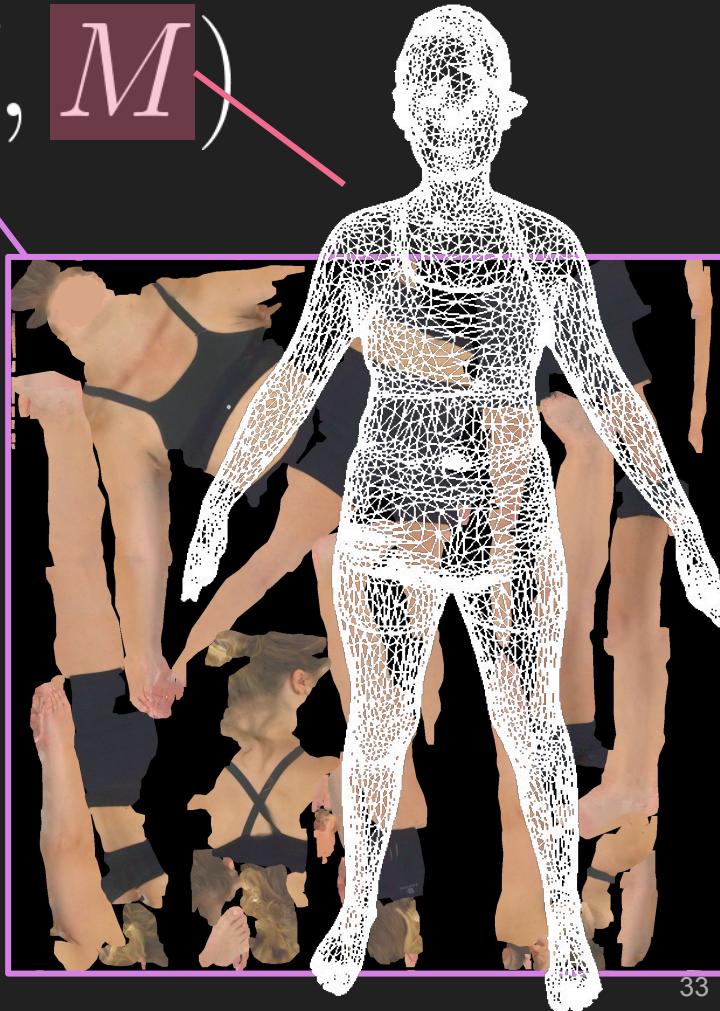


Rendering

$$x = R(\kappa, T, M)$$



3D body



Rendering

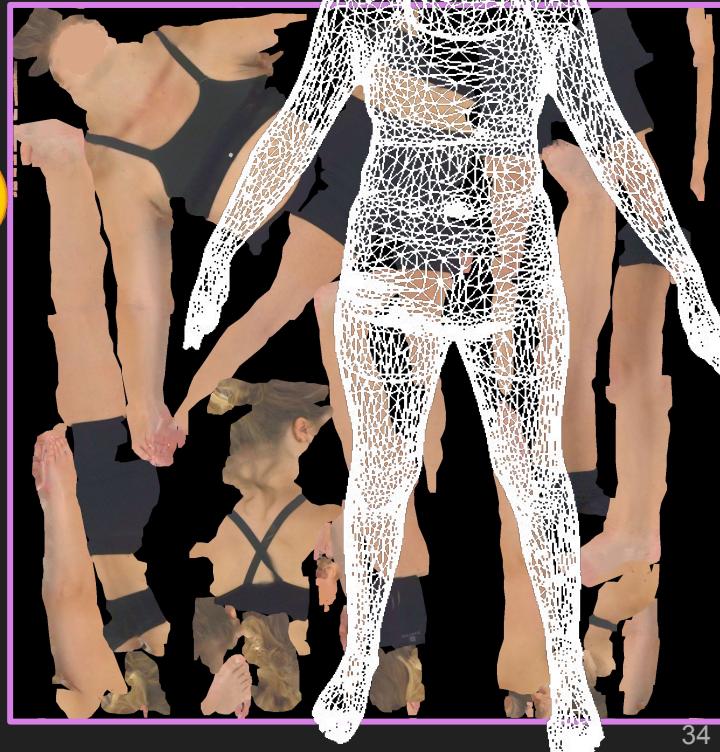
$$x = R(\kappa, T, M)$$



Rendered 2D image



3D body



Rendering

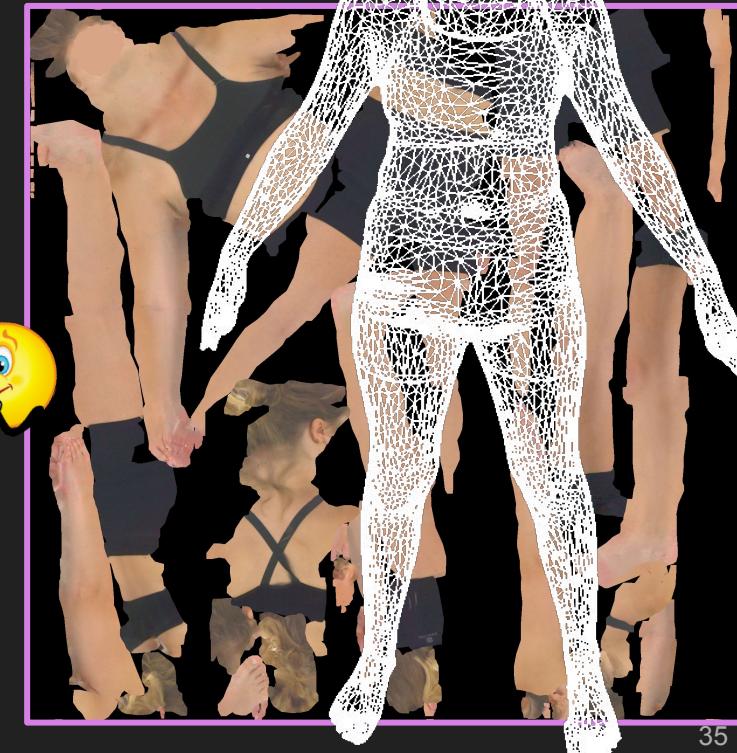
$$x = R(\kappa, T, M)$$



Rendered 2D image

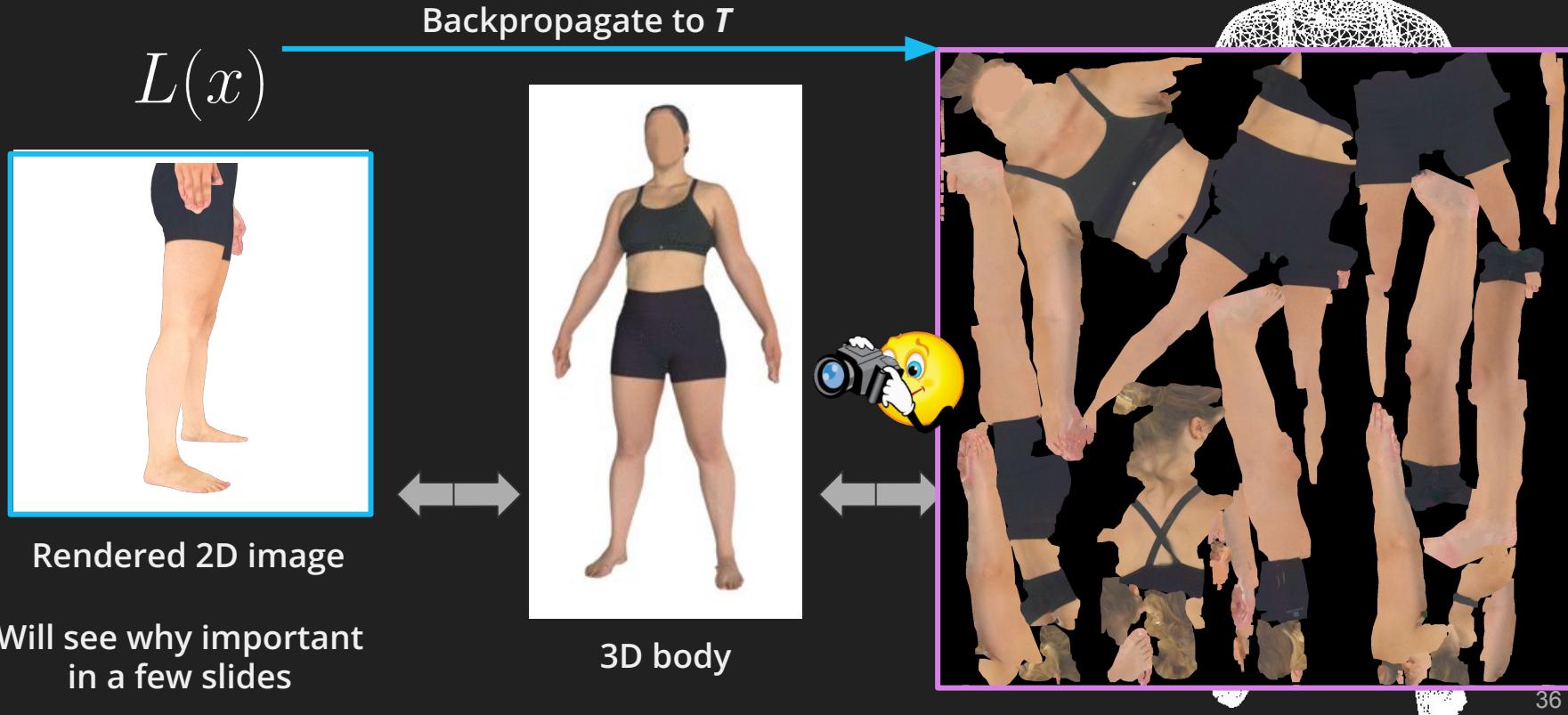


3D body



Differentiable Rendering

$$x = R(\kappa, T, M)$$



Differentiable Rendering

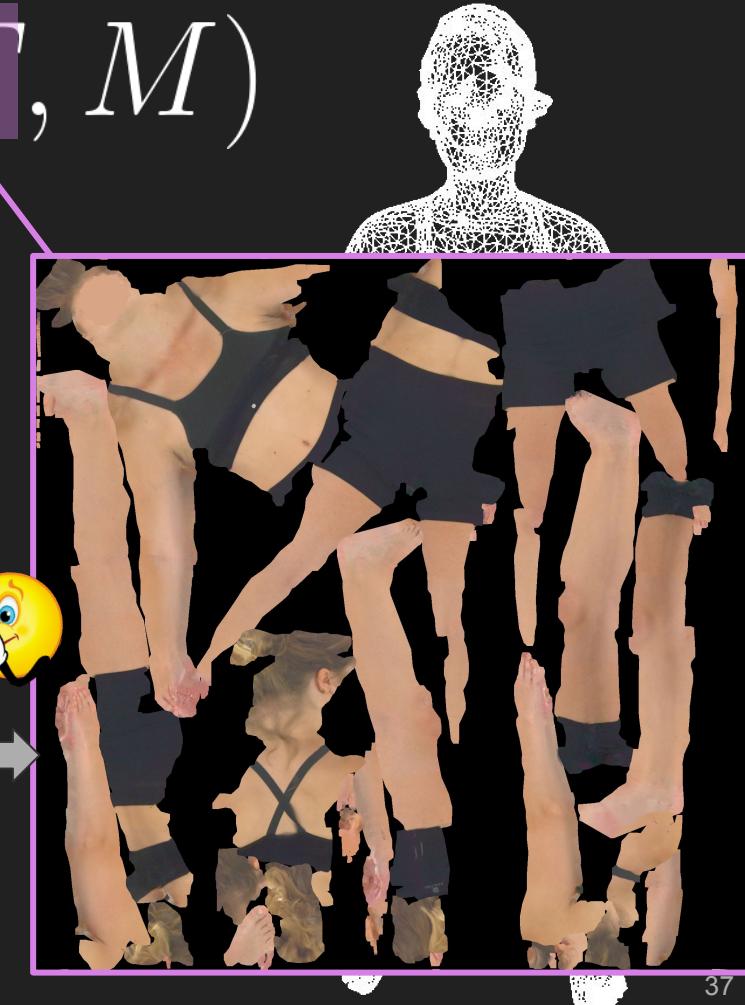
$$x = R(\kappa, T, M)$$



Rendered 2D image



3D body



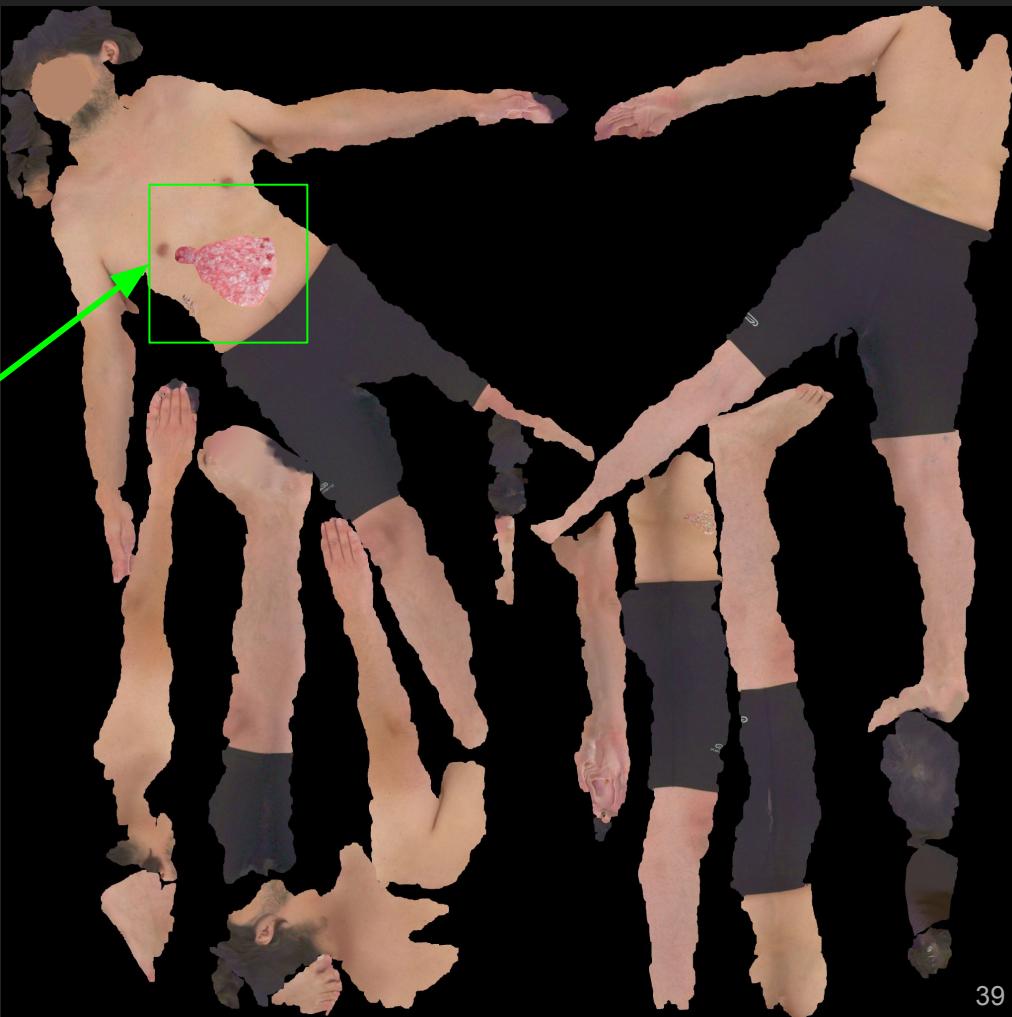
Transfer Real Lesion onto Texture Image?

Real segmented lesion



Would render on the 3D body

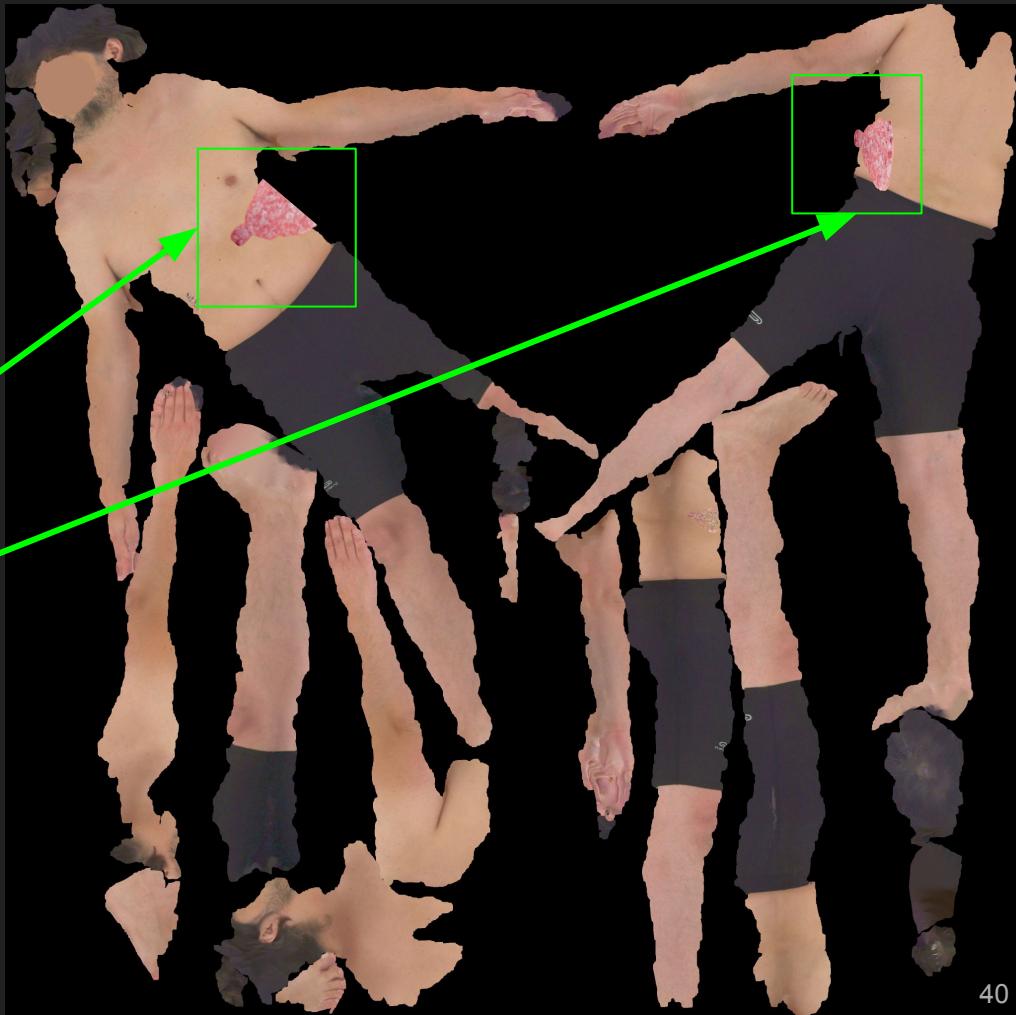
Real segmented lesion



Would render on the 3D body

But placing the lesions is a challenge due to seams

Real segmented lesion



Blending Lesions

Rendered image



$$x = R(\kappa, T, M)$$



Blending Lesions

Rendered image



Segmented real lesion



$$x = R(\kappa, T, M)$$

Compute blending loss $L(x, z)$ on rendered image and real lesion

$$L(x, z)$$

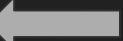
Zhang et. al., Deep Image Blending. 2020

Blending Lesions

Rendered image

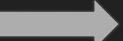


Segmented real lesion



$$x = R(\kappa, T, M)$$

Compute blending loss $L(x, z)$ on rendered image and real lesion



$$T^* = \operatorname{argmin}_T L(x, z)$$

Update the texture image T to minimize the loss



Zhang et. al., Deep Image Blending. 2020

Before Blending Lesions



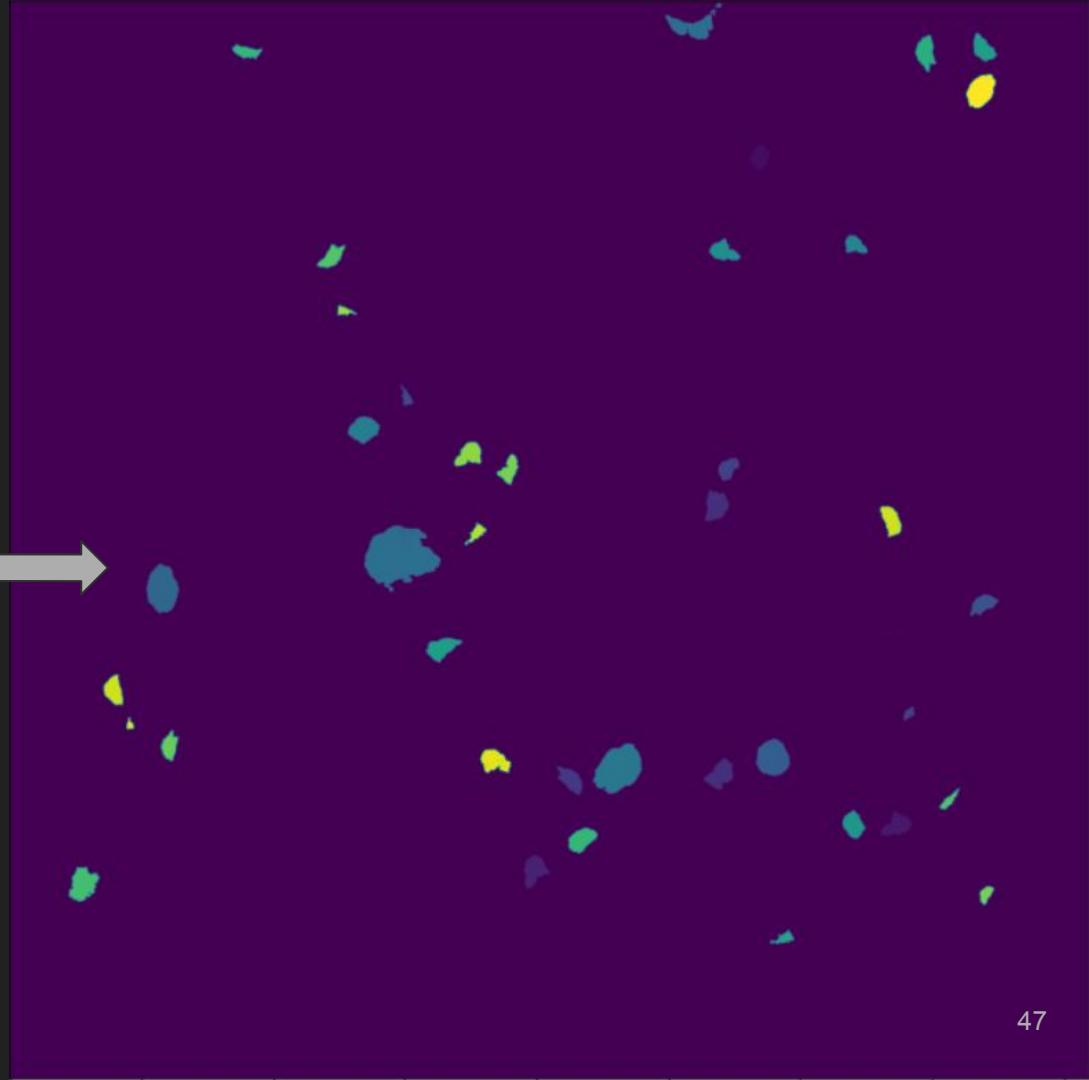
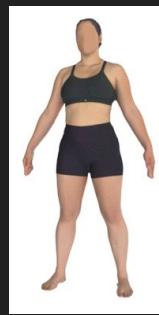
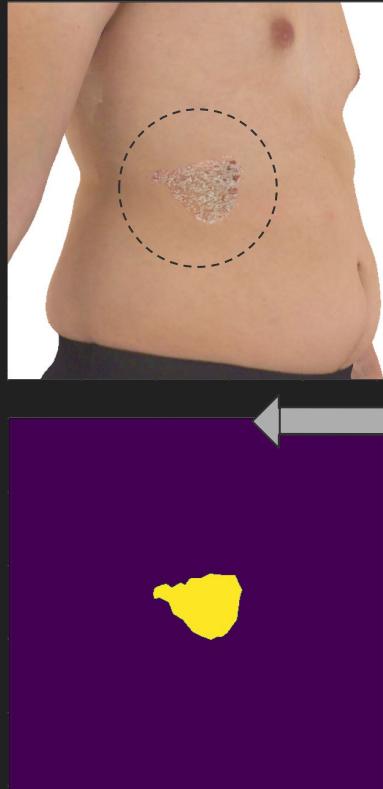
After Blending Lesions



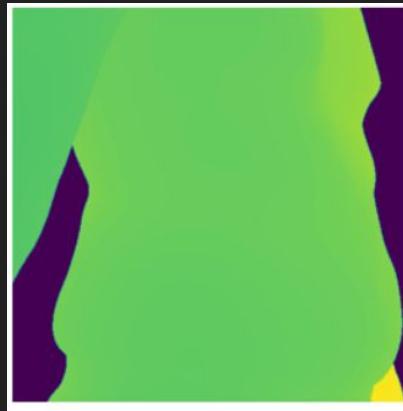
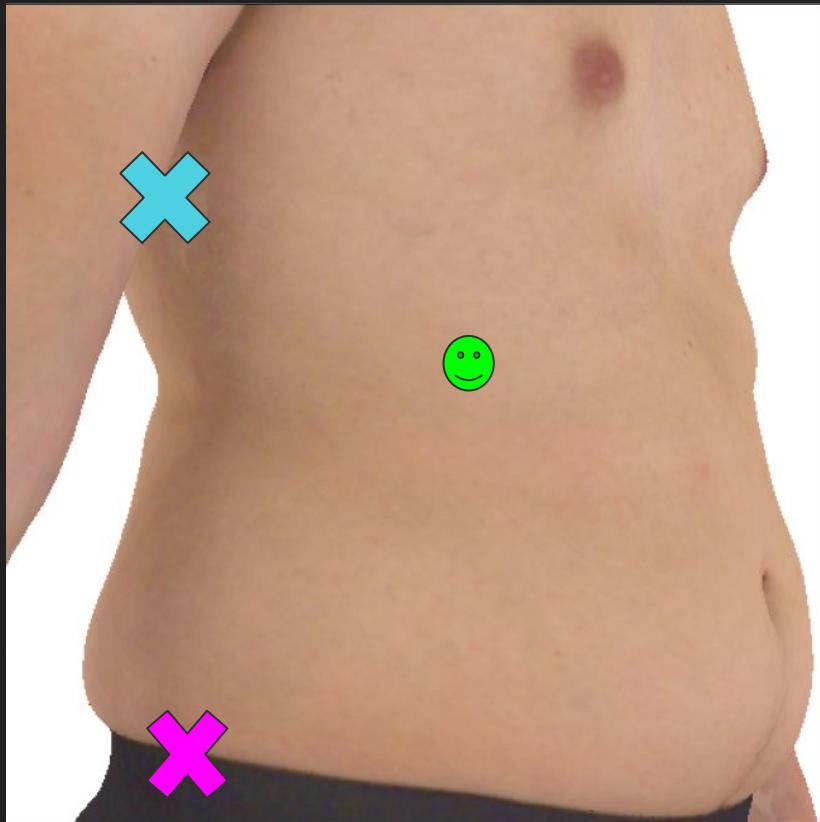
After Blending Lesions



Lesion Segmentations



Placing the Lesion: Depth and Clothing



Depth: distance to camera

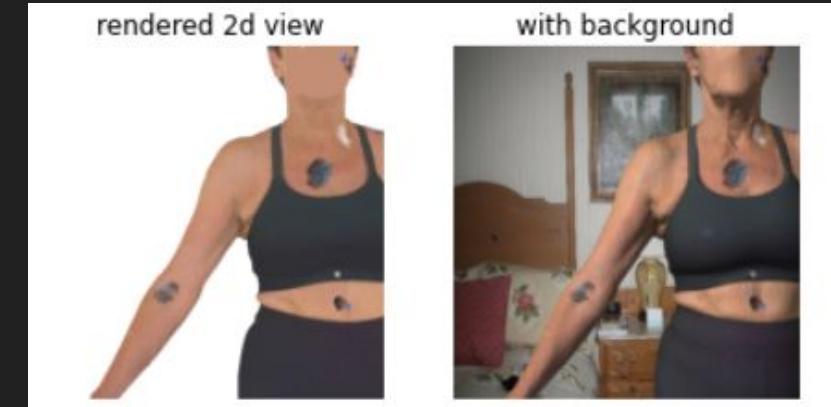
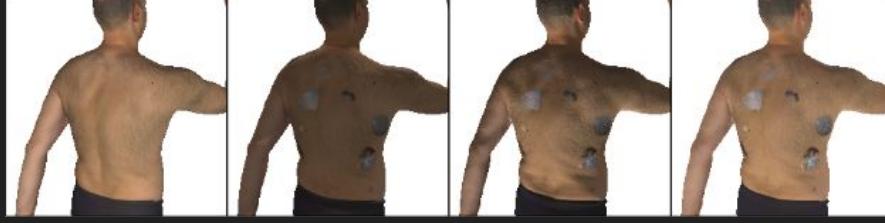
Avoid areas with large depth changes



Segmented Clothing



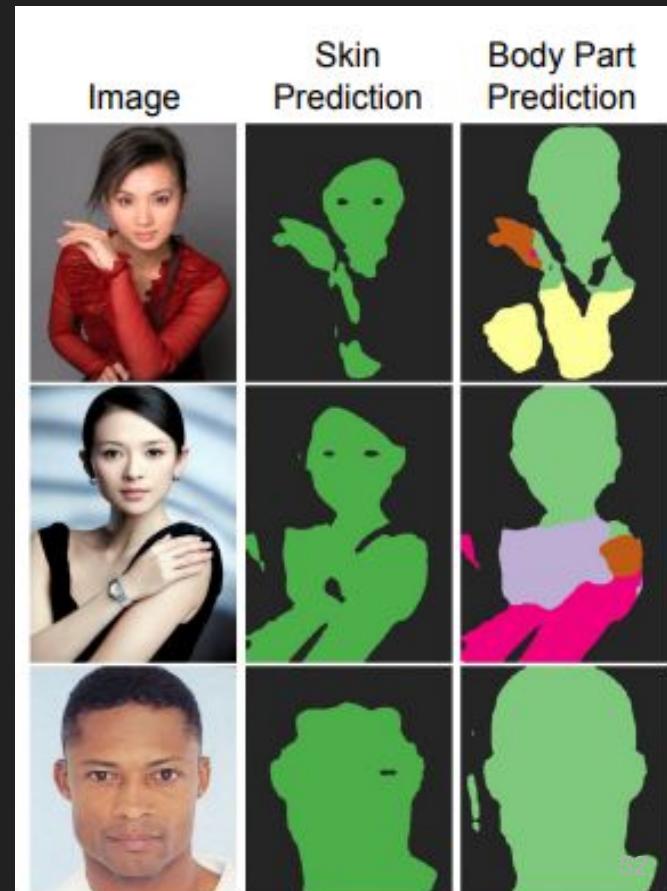
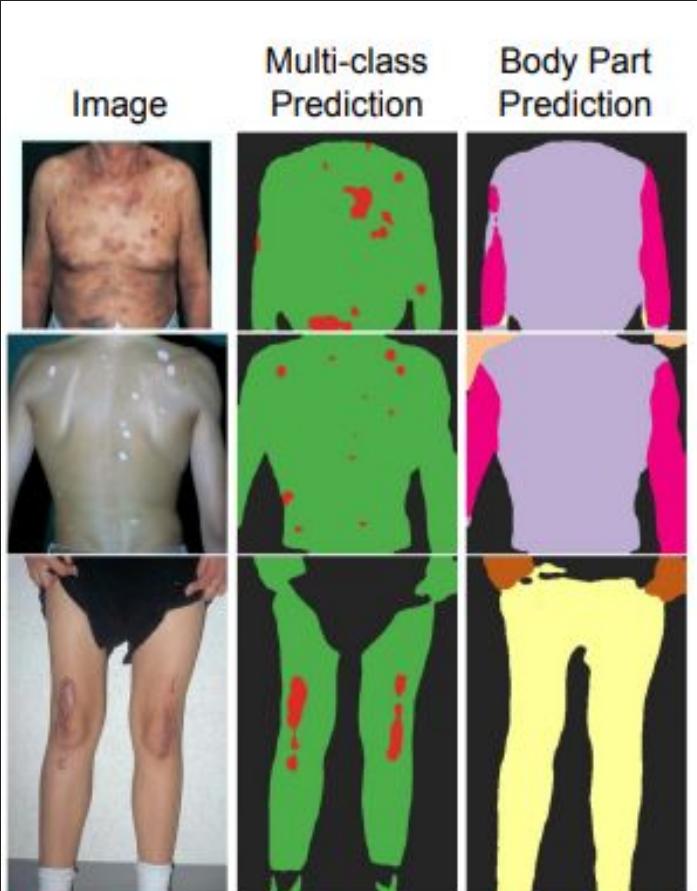
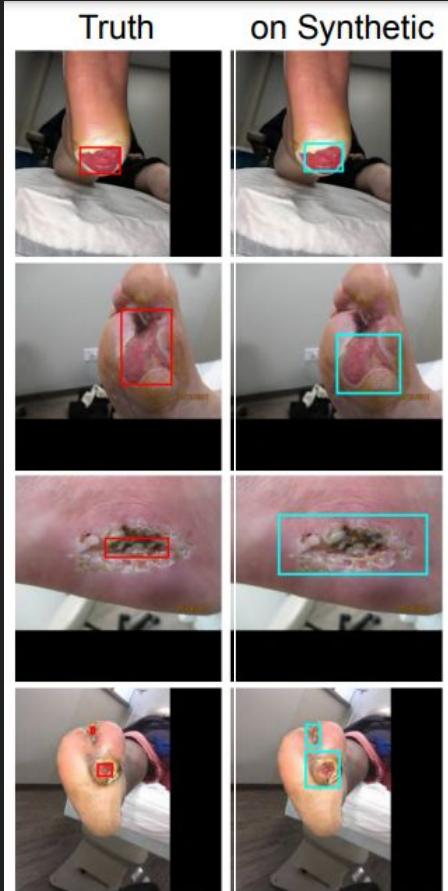
3D Scene Parameters and Backgrounds



Create 2D labelled datasets from 3D data for ML



Qualitative Results: train on synthetic, test on real

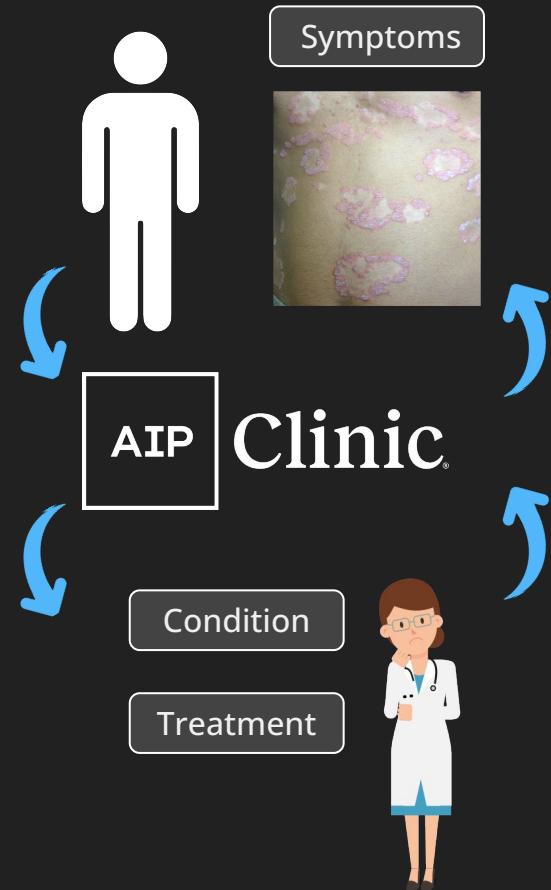




Web-based platform in Hungary,
Slovakia, and Spain

User sends a photo and symptoms to
our platform, AI processes the case,
forward to a human clinician

Human clinician reviews and returns
a skin condition and a treatment



Online Regional Application

Free pilot in Hungary with Semmelweis University

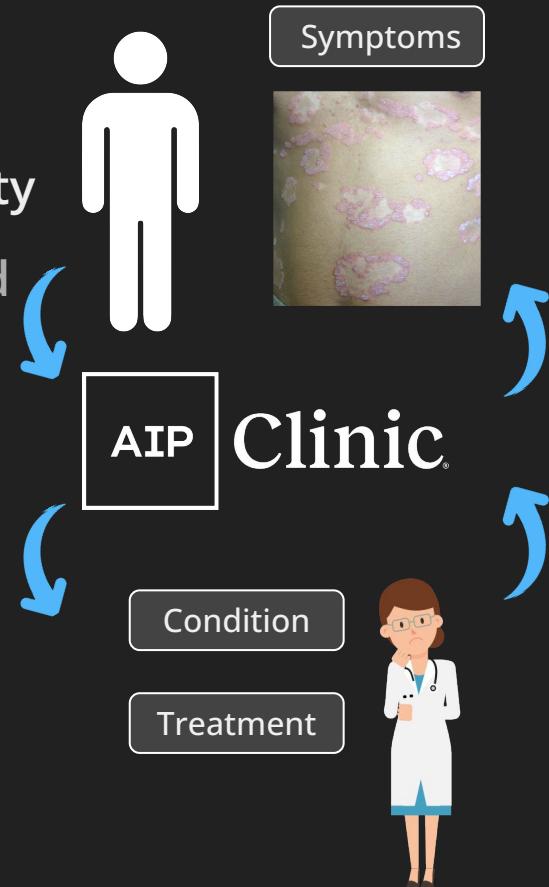
- Large public interest with ~30,000 registered users in ~6 months in 2022

Hungary: Paid service direct to users

Slovakia: Through an insurance company

Spain: Recently opened for direct users

Partner with clinicians in the region



User Statistics

Age	Hungary
0 - 25	14%
25 - 50	53%
50 - 75	29%
75+	4%

30%+ of users
aged 50+

Fitzpatrick	Hungary
I - II	81.9%
III - IV	17.9%
V - VI	0.2%

Most Fitzpatrick I - II
Some Fitzpatrick III-VI

	Hungary	Slovakia
Female	56%	64%
Male	44%	36%

Majority female users,
especially in Slovakia

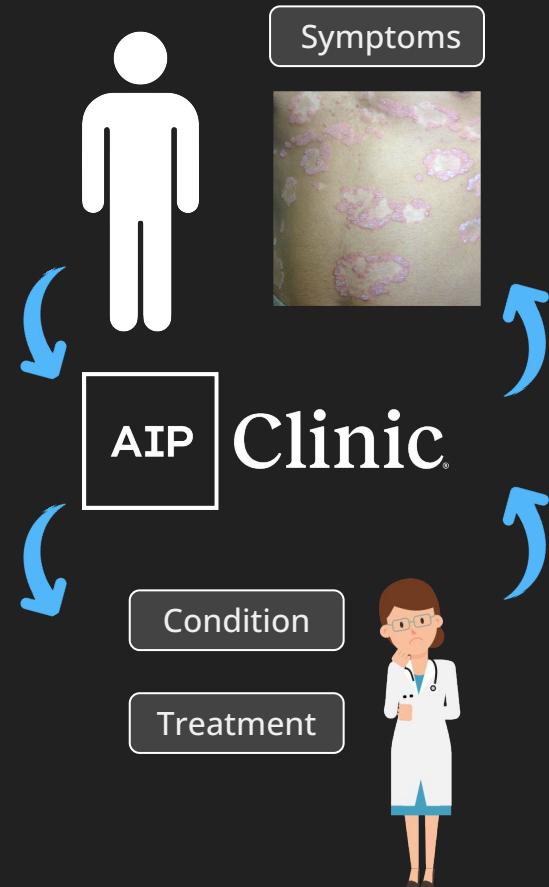
Machine Learning Use

Quality check for low quality images

- Prompt users to retake images immediately
- Limits low quality images that reach clinicians

Suggest skin conditions to the clinician

- Uses image and the symptoms (e.g., itchy)
- Clinicians see a variety of plausible conditions
- Limits clinician effort searching through hundreds of conditions



Common Conditions & Treatments

Rank	Hungary (Free pilot)	Hungary (Paid Service)
1	Common Mole	Contact Dermatitis
2	Seborrheic Keratosis	Seborrheic Keratosis
3	Atypical Mole	Atypical Mole
4	Contact Dermatitis	Dyshidrotic Eczema
5	Dermal Nevus	Ringworm

Treatment	Hungary (Free)	Hungary (Paid)
Clinic visit	61%	30%
Prescription	22%	62%
Over-the-counter	15%	7%
None	2%	1%

Common Conditions & Treatments

Rank	Hungary (Free pilot)	Hungary (Paid Service)
1	Common Mole	Contact Dermatitis
2	Seborrheic Keratosis	Seborrheic Keratosis
3	Atypical Mole	Atypical Mole
4	Contact Dermatitis	Dyshidrotic Eczema
5	Dermal Nevus	Ringworm

Benign moles occurred frequently in the free pilot, but less frequently in the paid service

Treatment	Hungary (Free)	Hungary (Paid)
Clinic visit	61%	30%
Prescription	22%	62%
Over-the-counter	15%	7%
None	2%	1%

Pilot: 60% referred to in-person clinic
(early hesitation of clinicians + many moles)

Paid: 30% referred to in-person clinic
(fewer moles)

Integrating Regional Prescriptions

Prescriptions appropriate to the region

- Regional prescription database

Ensure patients can access and fulfill the prescriptions

- Integrate with regional e-health systems
- Allow patients to pick up prescriptions from a local pharmacy

Treatment	Hungary (Free)	Hungary (Paid)
Clinic visit	61%	30%
Prescription	22%	62%
Over-the-counter	15%	7%
None	2%	1%

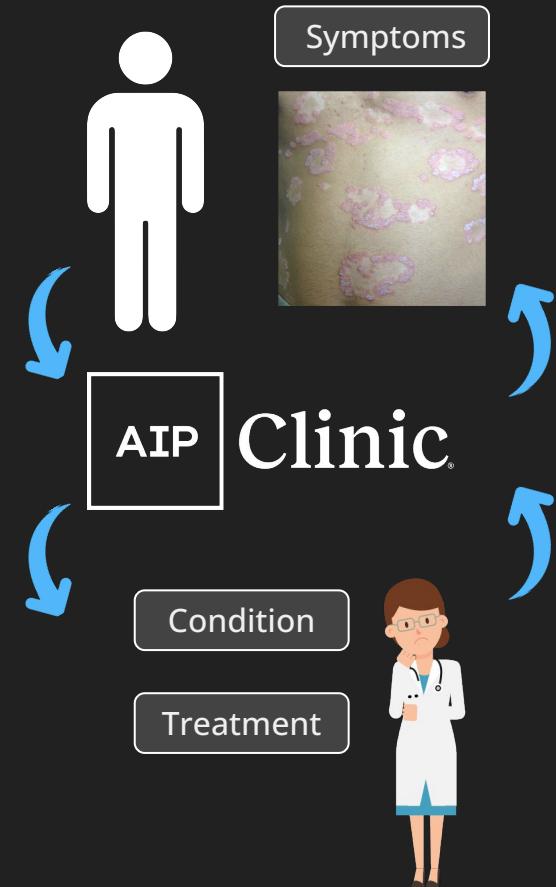
Closing Thoughts

Diagnosis is one step

- Patients need treatments
- ML systems to predict treatments?
- 1 diagnosis can have many treatments
- Treatments may offer insights into severity

ML tools to support clinicians and users

- Humans drive the decision steps



Summary

2D dermatology images

Detecting and tracking moles on 3D body scans

Blending real 2D images on 3D meshes and creating synthetic dataset

Dermatology application used in Europe



End