

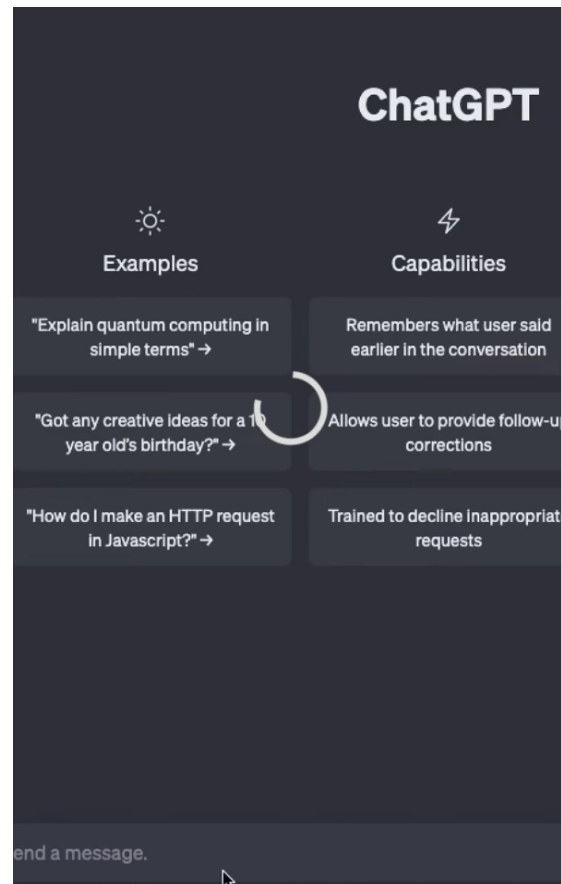
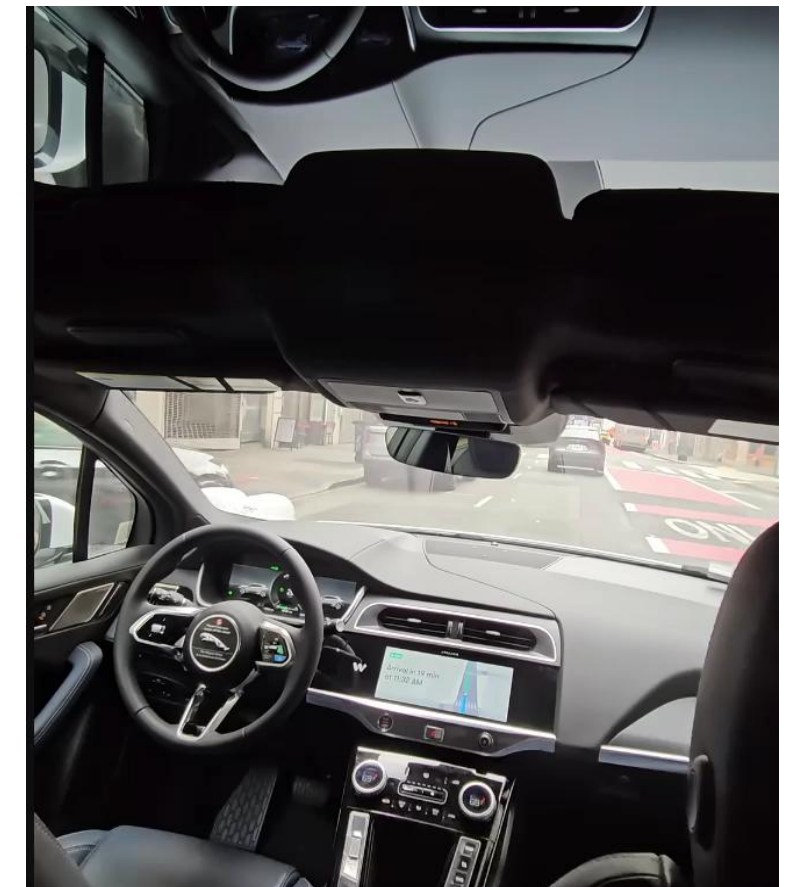
Come Impara l'Intelligenza Artificiale

Dati, paradigmi di apprendimento e ricerca applicata all'imaging dentale

AI in Medical Imaging · How AI Learns · What We Do · Take-Home

Federico Bolelli

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An AI algorithm learns **only from the data** it is given, no one “writes” the rules.

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1 DATA

Thousands of (expert)-labeled examples

Quantity

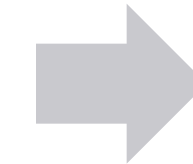
Enough cases to cover normal variation

Quality

Correct, consistent expert labels

Variety

Different patients, devices, clinics



2 TRAINING

The algorithm finds the patterns in the data

It makes a prediction, compares it with the expert label and corrects itself, millions of times.

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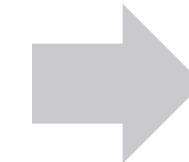
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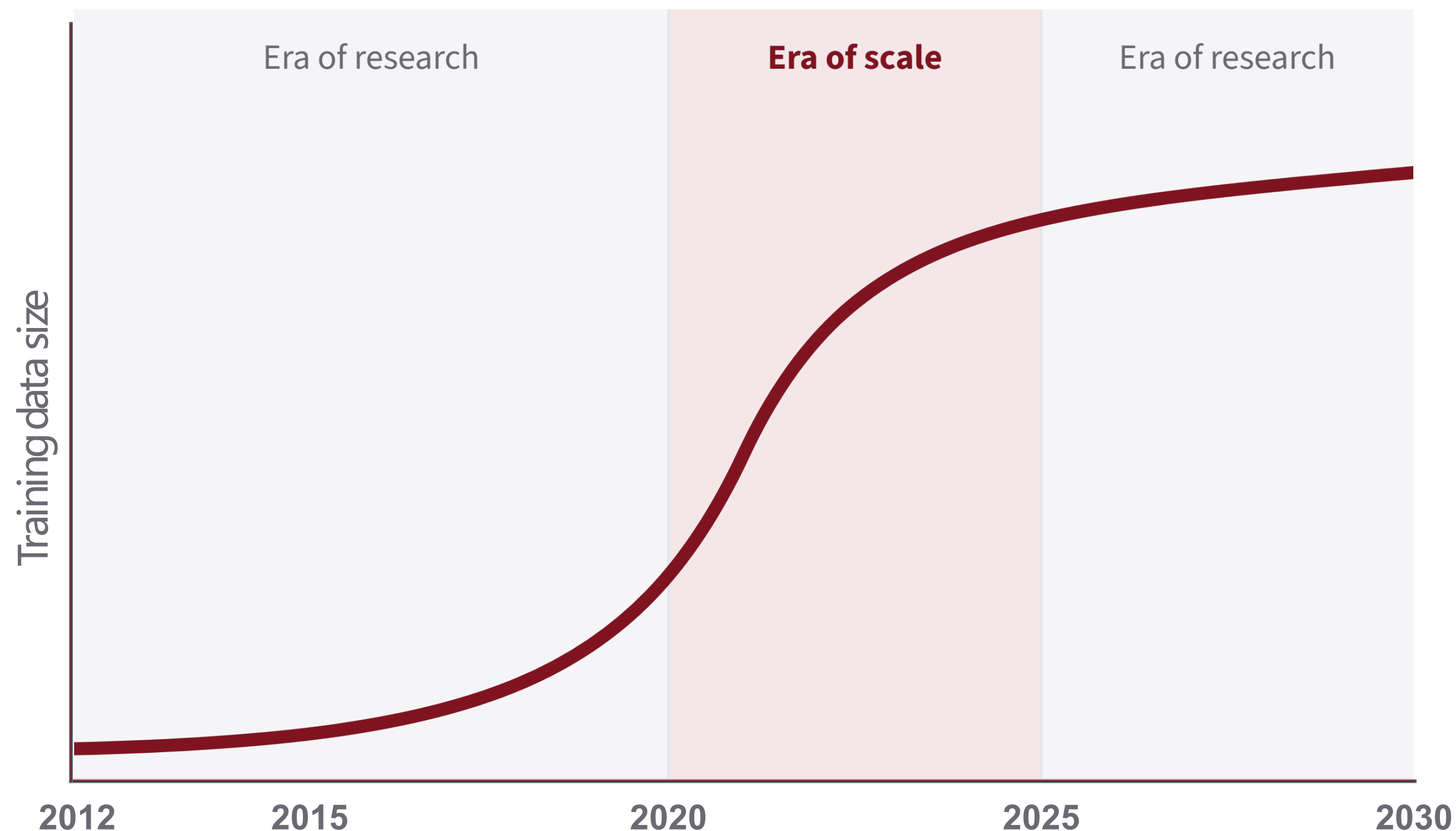
The model can never be better than its data: **biased or wrong data in, biased or wrong model out.**

Current State of AI in Medical Imaging

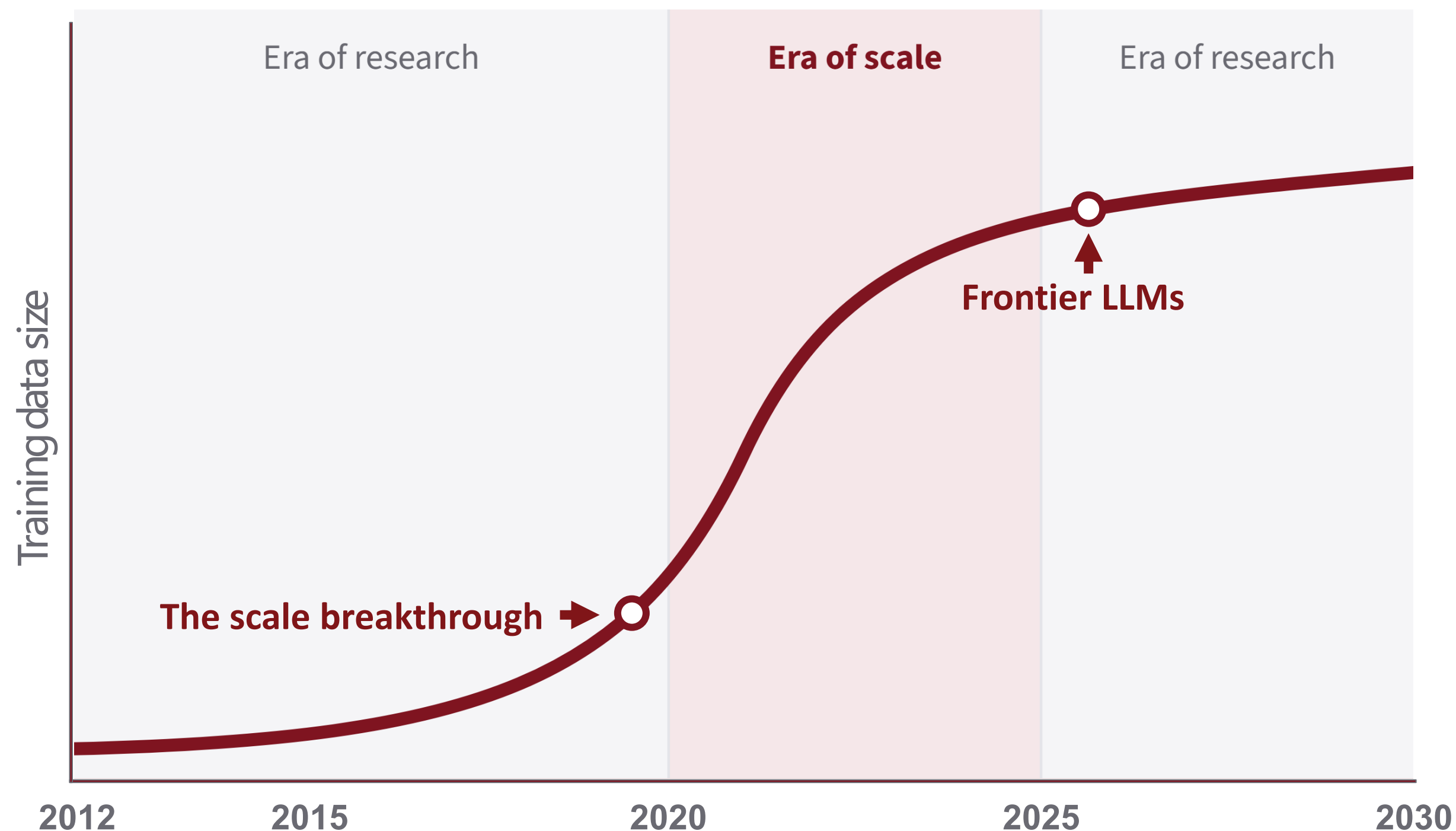
AI works almost everywhere. Why not (yet) in the clinic?



General models crossed into the **era of scale**.



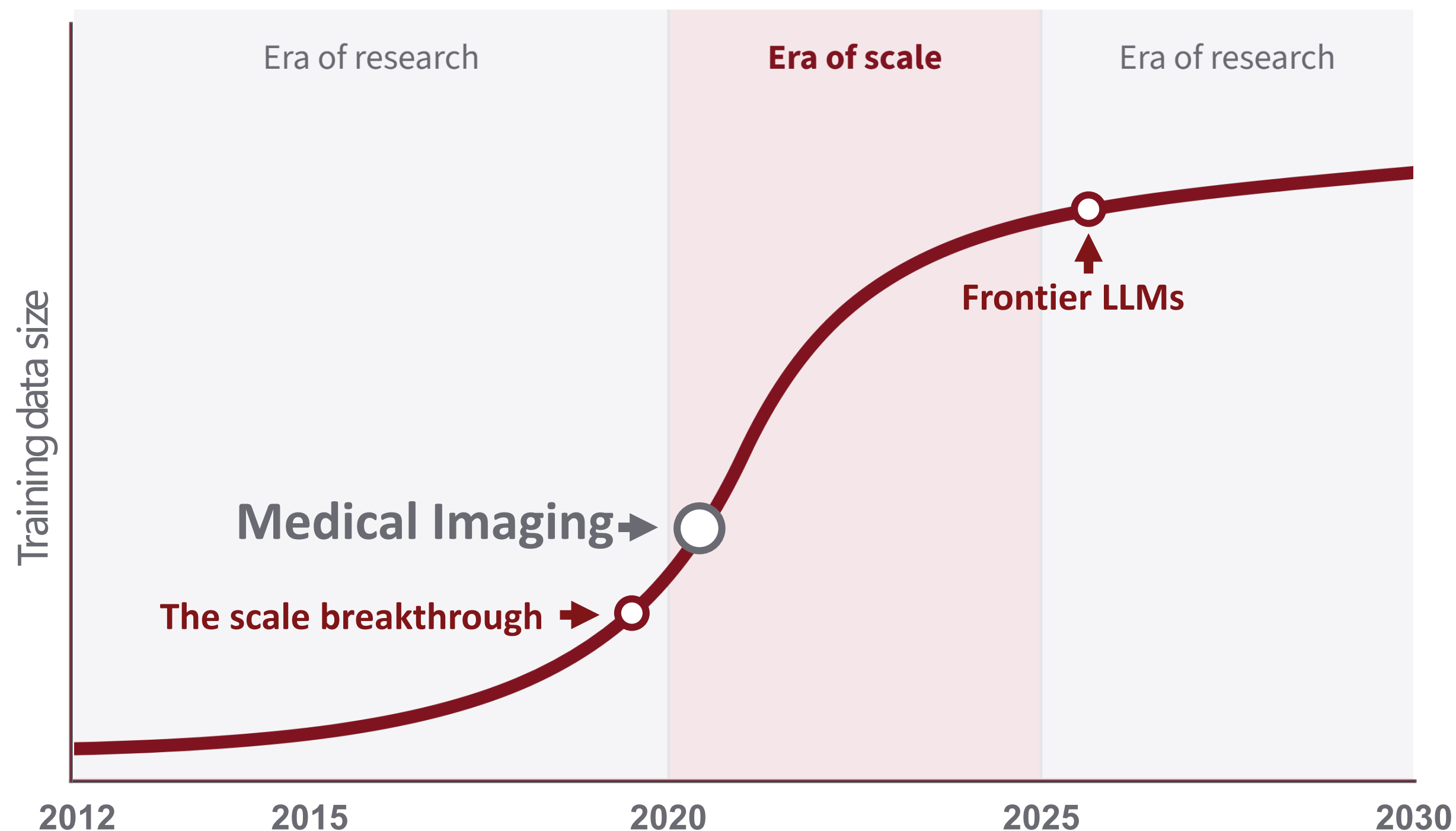
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Counts as reported by the authors: WebLI (SigLIP 2), PMC-15M (BiomedCLIP), SA-1B (SAM), MedSAM, ImageNet-21k, RadImageNet.

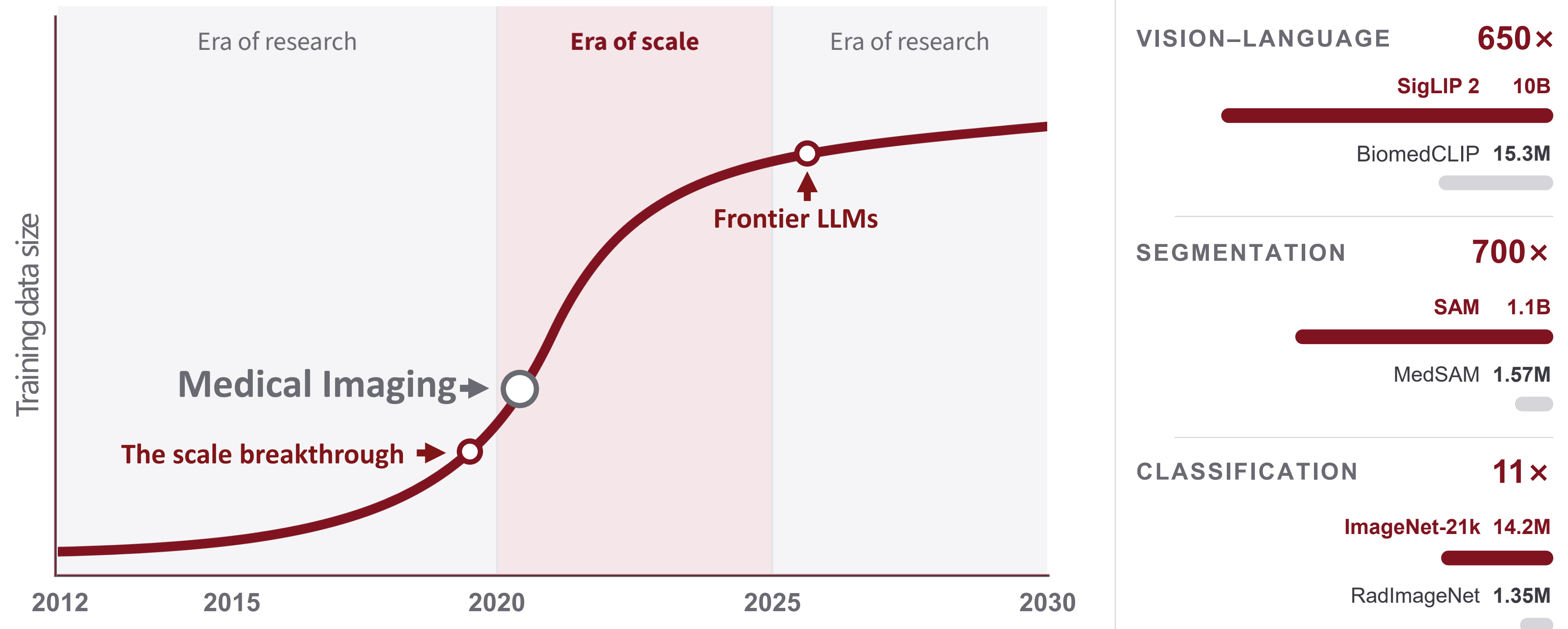
[1] Curtis P. Langlotz - Toward a Radiology Foundation Model

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Why Is Medical Imaging AI Still Behind General Models?

General models crossed into the **era of scale**.



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WHERE IT ALREADY WORKS

PATHOLOGY — BREAST, WSI

0.994
algorithm

0.884
pathologist

AUC of the best algorithm against the best pathologist in a time-constrained diagnostic setting. Seven of 32 algorithms exceeded a panel of 11 pathologists.

DERMOSCOPY — MELANOMA

0.86
CNN

0.79
dermatologists

ROC AUC of a CNN against the mean of 58 dermatologists in a reader study.

BREAST HISTOLOGY

99%
panel of four

85%
single observer

Accuracy on benign versus malignant discrimination on previously unseen slides; pooling four independent observers raises it to 99%.

[1] Ehteshami Bejnordi, Babak, et al. "Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer" *Jama* 2017.

[2] Haenssle, Holger A., et al. "Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists." *Annals of Oncology* 2018.

[3] Levenson et al., "Pigeons (*Columba livia*) as Trainable Observers of Pathology and Radiology Breast Cancer Images" *PLoS ONE* 2015.

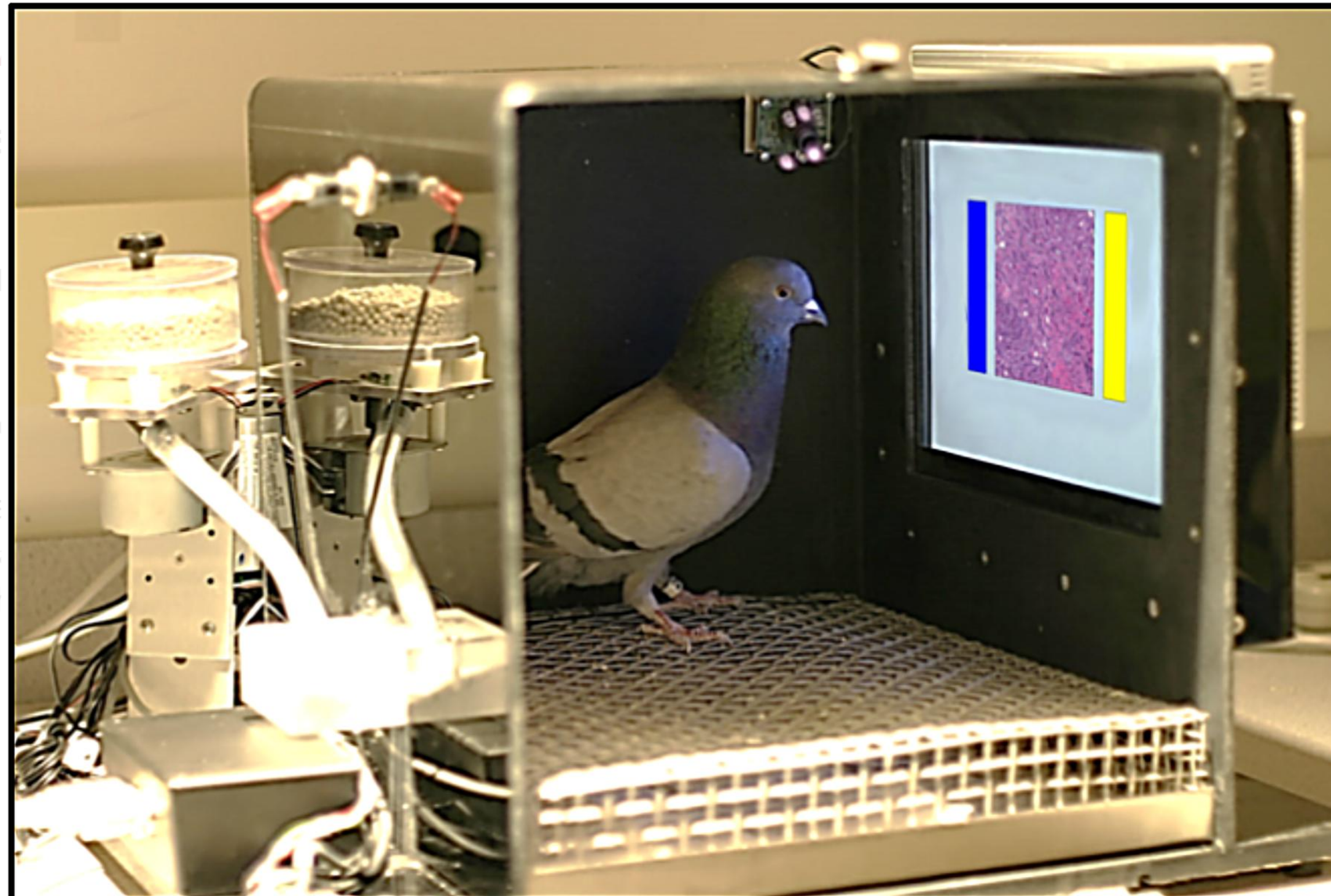
WHERE IT ALREADY WAS

PATHOLOGY — BREAST

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AUC of the best algorithm a pathologist in a time-constrained setting. Seven of 32 algorithms panel of 11 pathologists.



PATHOLOGY

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single observer

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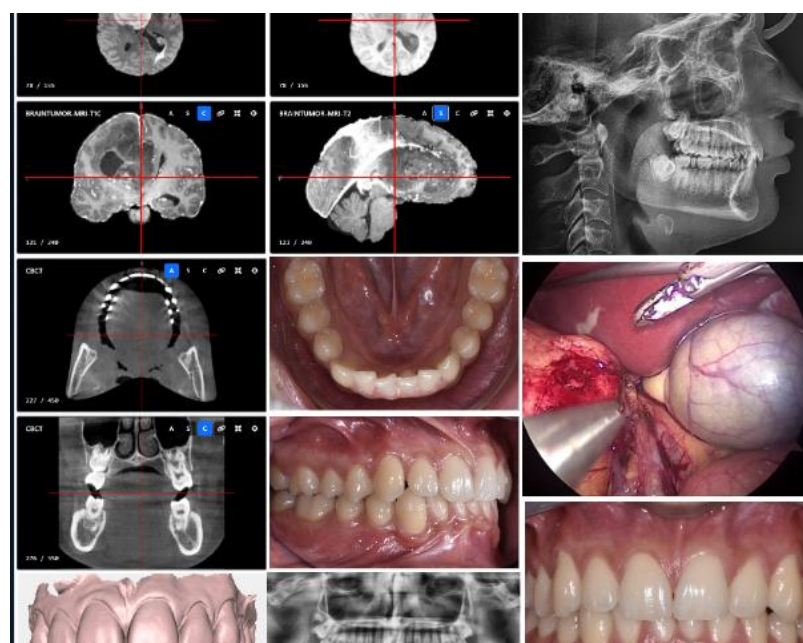
[3] Levenson et al., "Pigeons (*Columba livia*) as Trainable Observers of Pathology and Radiology Breast Cancer Images" *PLoS ONE* 2015.

The Data Problem

Scarce, private, hard to label: why data are the real bottleneck.



The algorithms exist. The data they need are not in the right shape.



01

Scarce & scattered

Small private datasets, acquired differently in every clinic.



02

Privacy & GDPR

Faces, scans and records are personal data: sharing them is hard.



03

Expert labels

Every annotation costs specialist time: your time.



04

Complex data

3D volumes and meshes, not photos: millions of voxels per patient.

Benchmarks are **the foundation** of medical imaging AI.

Standardized acquisition

Shared protocols, cases from **multiple institutions**.



Multi-expert annotation

Several clinicians label each case, not a single reader.



Inter-clinician agreement

Expert agreement sets **the reference standard** for AI.



[1] B. H. Menze, et al. "The Multimodal Brain Tumor Image Segmentation Benchmark (BraTS)." IEEE TMI 2015.

[2] A. L. Simpson, M. Antonelli, et al. "A large annotated medical image dataset for the development and evaluation of segmentation algorithms." 2019.

[3] P. Bandi, et al. "From detection of individual metastases to classification of lymph node status at the patient level: the camelyon17 challenge." IEEE TMI (2018).

Several times, benchmark are released in the context of a **challenge: many teams, one clinical task, the same data, standardize evaluation.**

01

Release the data

Organizers publish expert-annotated cases and define the clinical task.

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Teams train

Groups worldwide train their AI algorithms on the public training set.

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03

Hidden test

Models are evaluated on a hidden test set and ranked with the same metrics.

#	User (Team)	Algorithm	Created	Mean Dice Average Position	Average (Position)	HD95 Average (Position)
1st	 ff741333 (Black_Myth)	toothfairy3_blackmyth	19 Aug. 2025	1	0.7981 ± 0.0640 (1)	88.7228 ± 32.3250 (1)
2nd	 thuengitmoi (TAIR Lab)	um2-final	19 Aug. 2025	2	0.7917 ± 0.0652 (2)	93.1873 ± 30.4327 (2)
3rd	 changkkk (sjtu_eiee_2-426lab)	ThirdTry	19 Aug. 2025	4	0.7705 ± 0.0754 (3)	104.5936 ± 37.2139 (5)

How AI Learns

Training, testing, and how much of the expert's time it takes.





The data: scans with doctor's labels

TRAINING SET

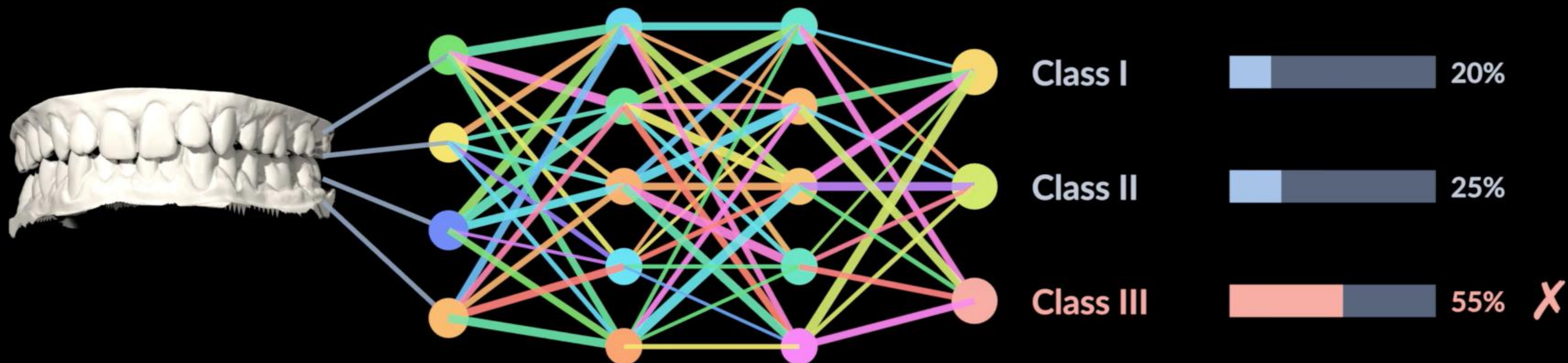


TEST SET

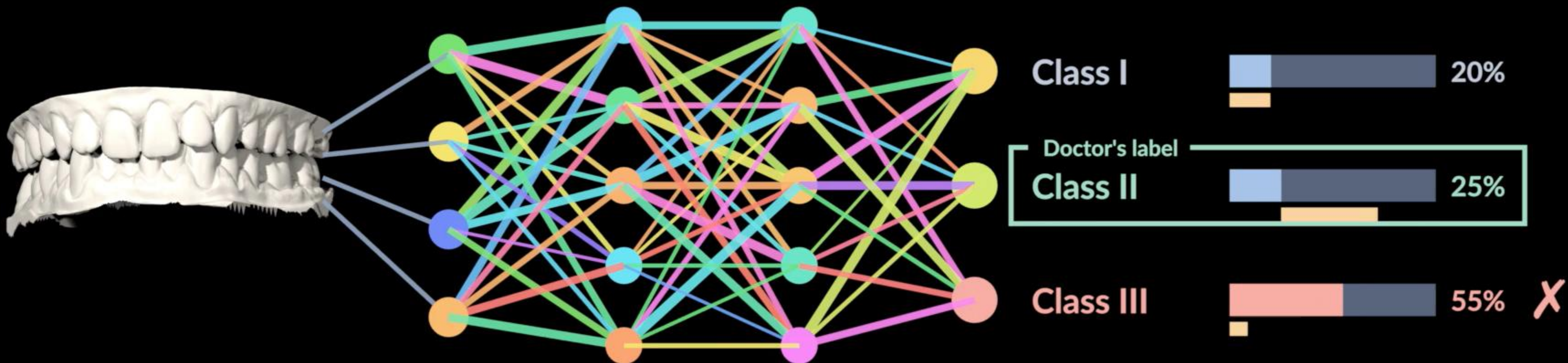




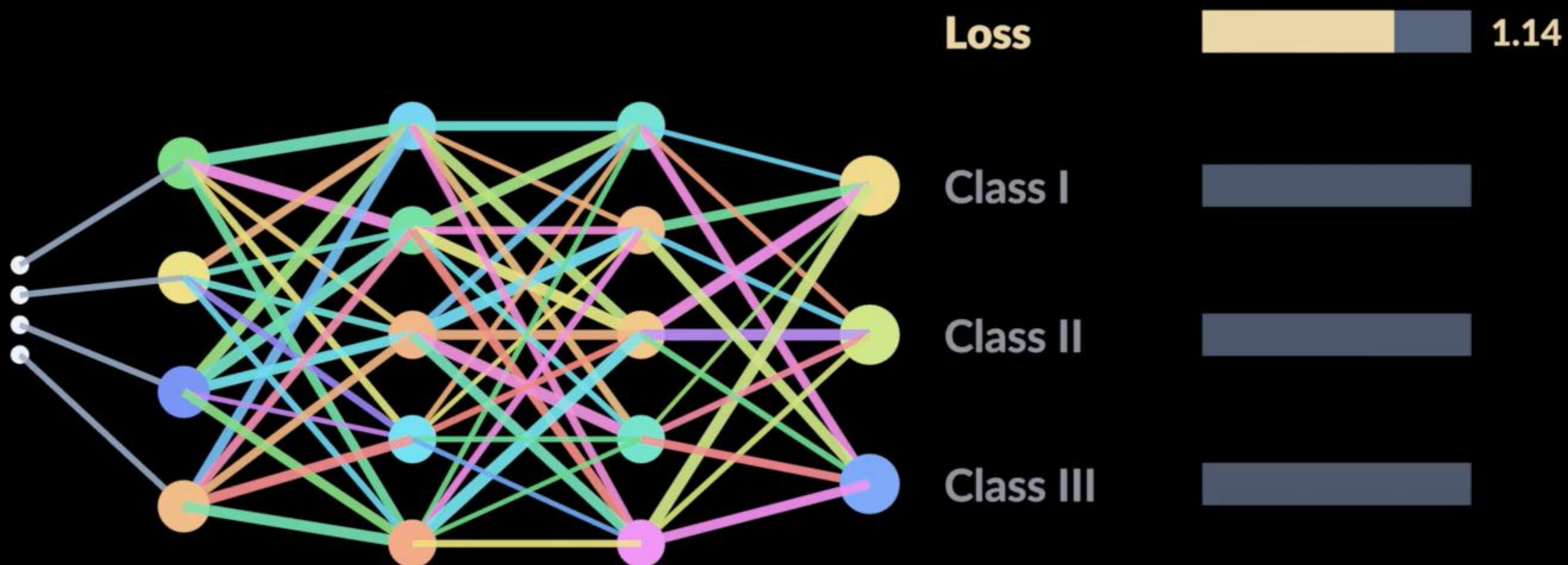
PHASE 1 • TRAINING



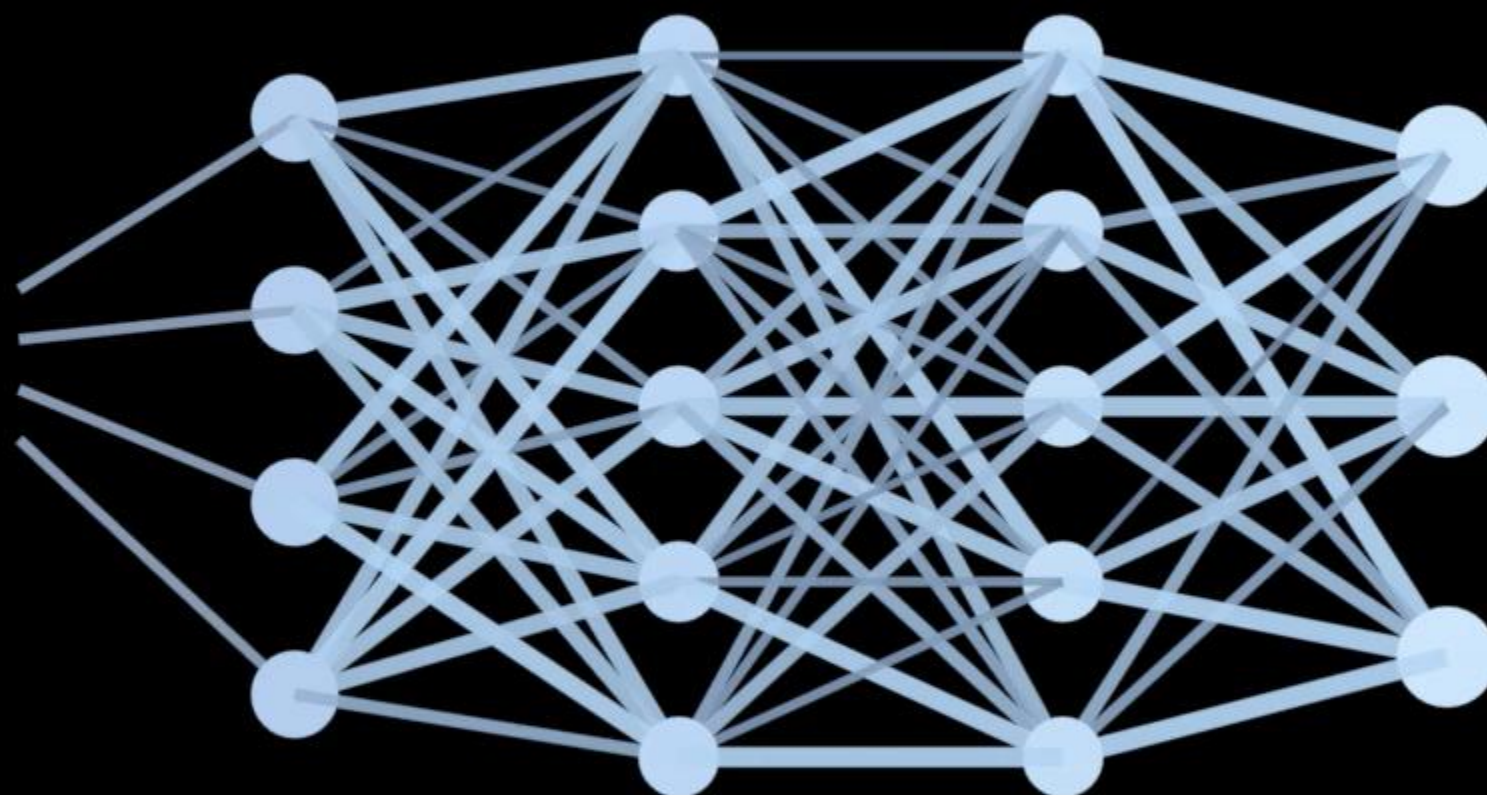
PHASE 1 • TRAINING



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Loss



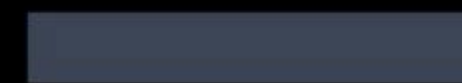
Class I



Class II



Class III



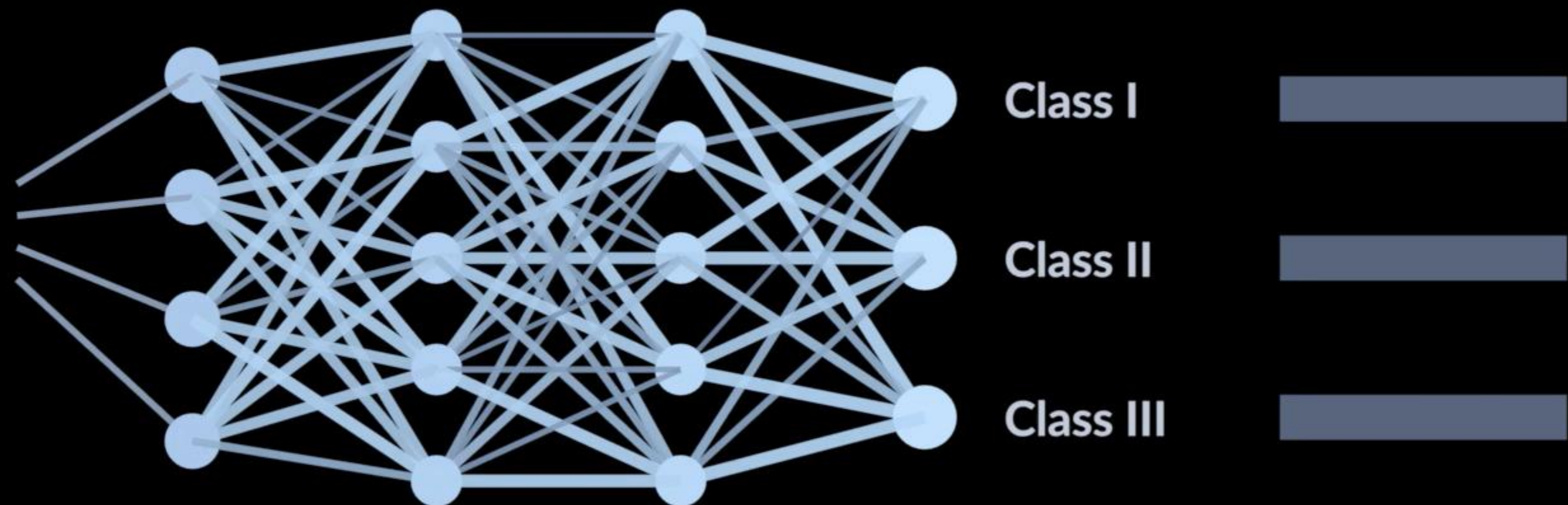


PHASE 2

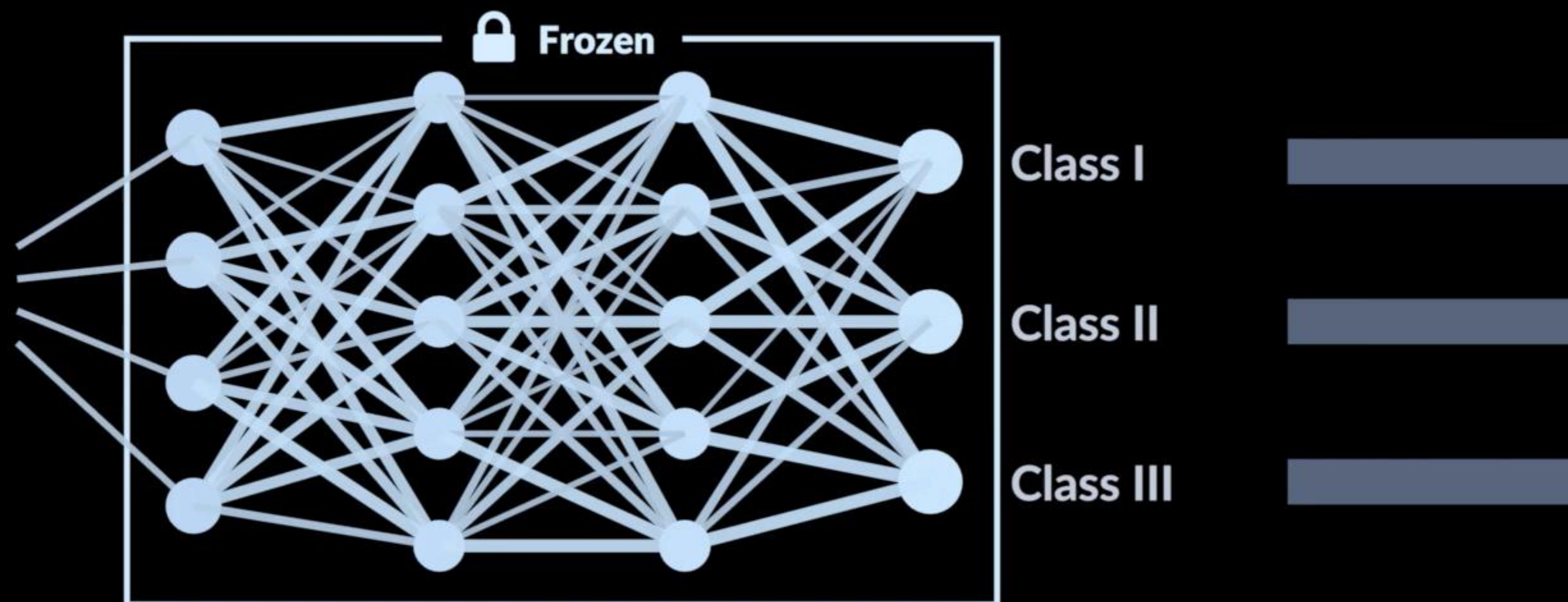
Test

New patients from the test set, never seen before

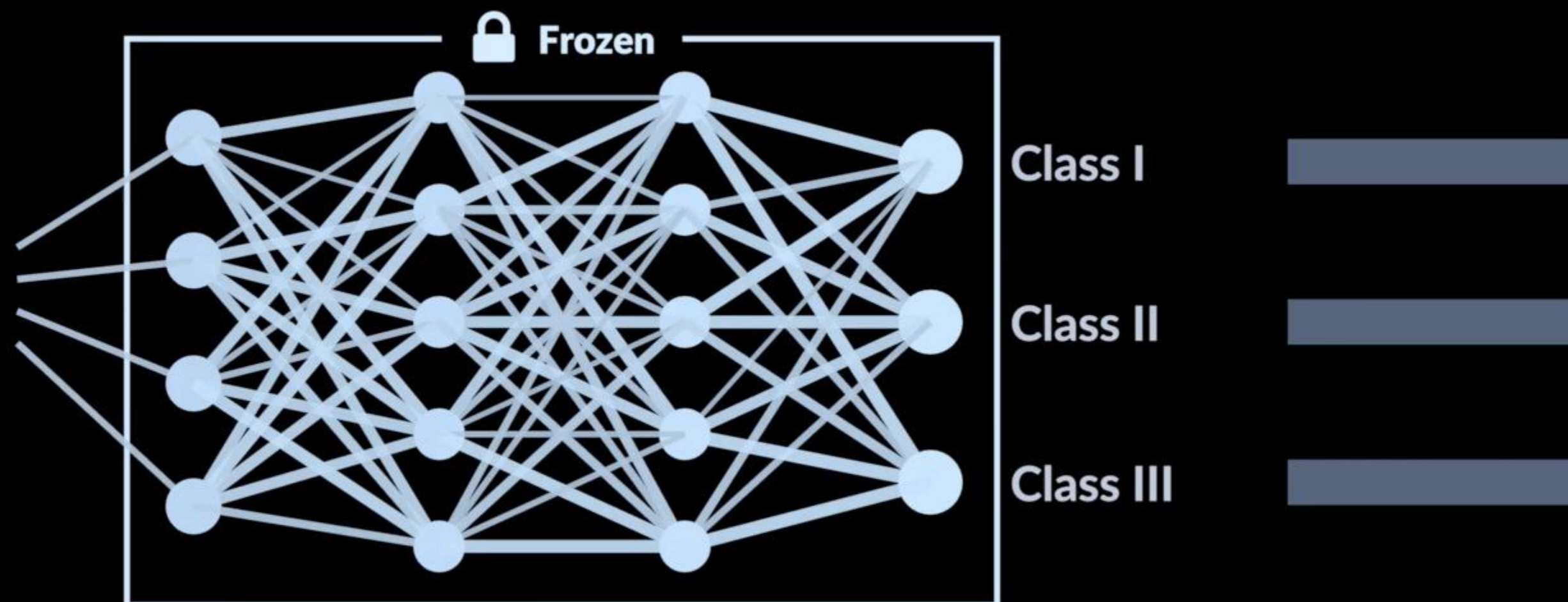
PHASE 2 • TEST



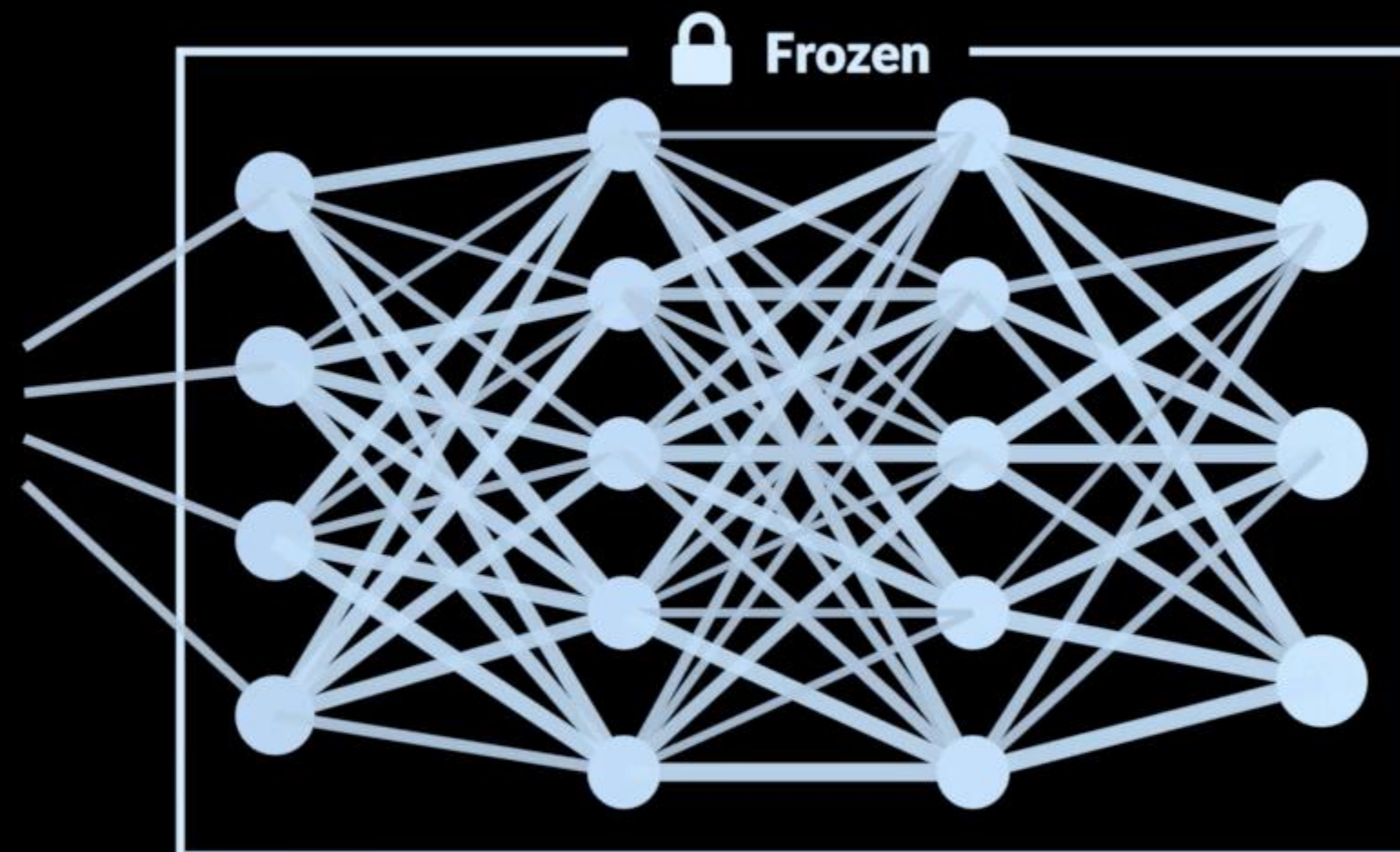
PHASE 2 • TEST



PHASE 2 • TEST



PHASE 2 • TEST

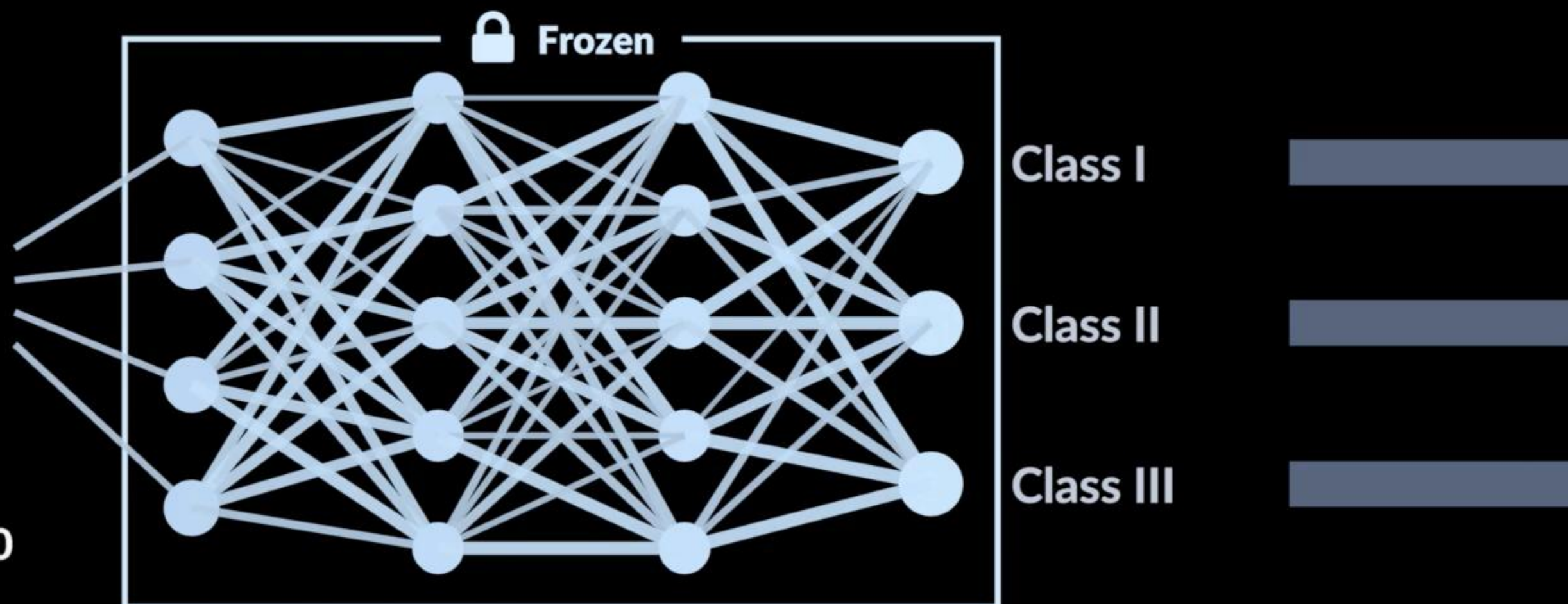


PHASE 2 • TEST

the whole test set ►►

Test patients: 200 / 200

✓ 174 ✗ 26



Each task needs metrics that answer **the clinical question**.

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CLASSIFICATION



Class I / **II** / III

Accuracy

Share of cases classified correctly. **Misleading if a condition is rare.**

Sensitivity (or recall)

Of the patients annotated "**positive**" to the condition, how many the model **finds**.

Positive predictive value (or precision)

Of the patients predicted "**positive**" to the condition, how many **really** has the condition.

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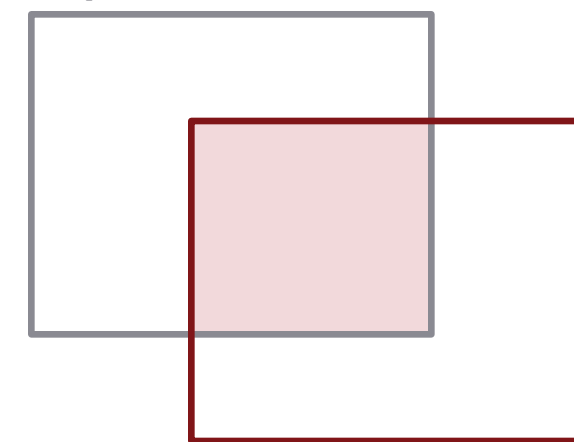
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DETECTION & SEGMENTATION



Expert



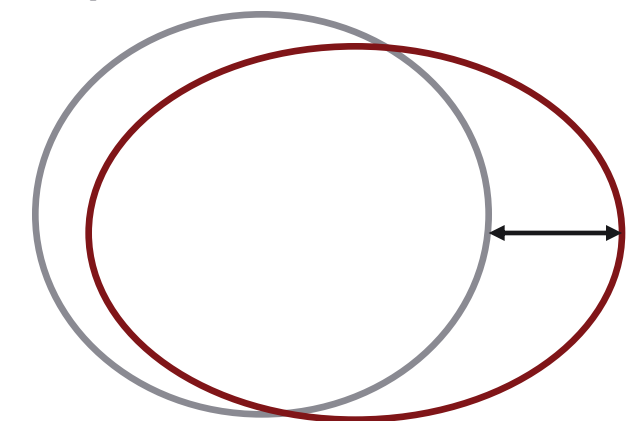
AI predicted

Overlap: IoU

Shared area of AI predicted and expert-annotated box or mask, out of their combined area.

1 = perfect match.

Expert



AI predicted

Boundary: HD95

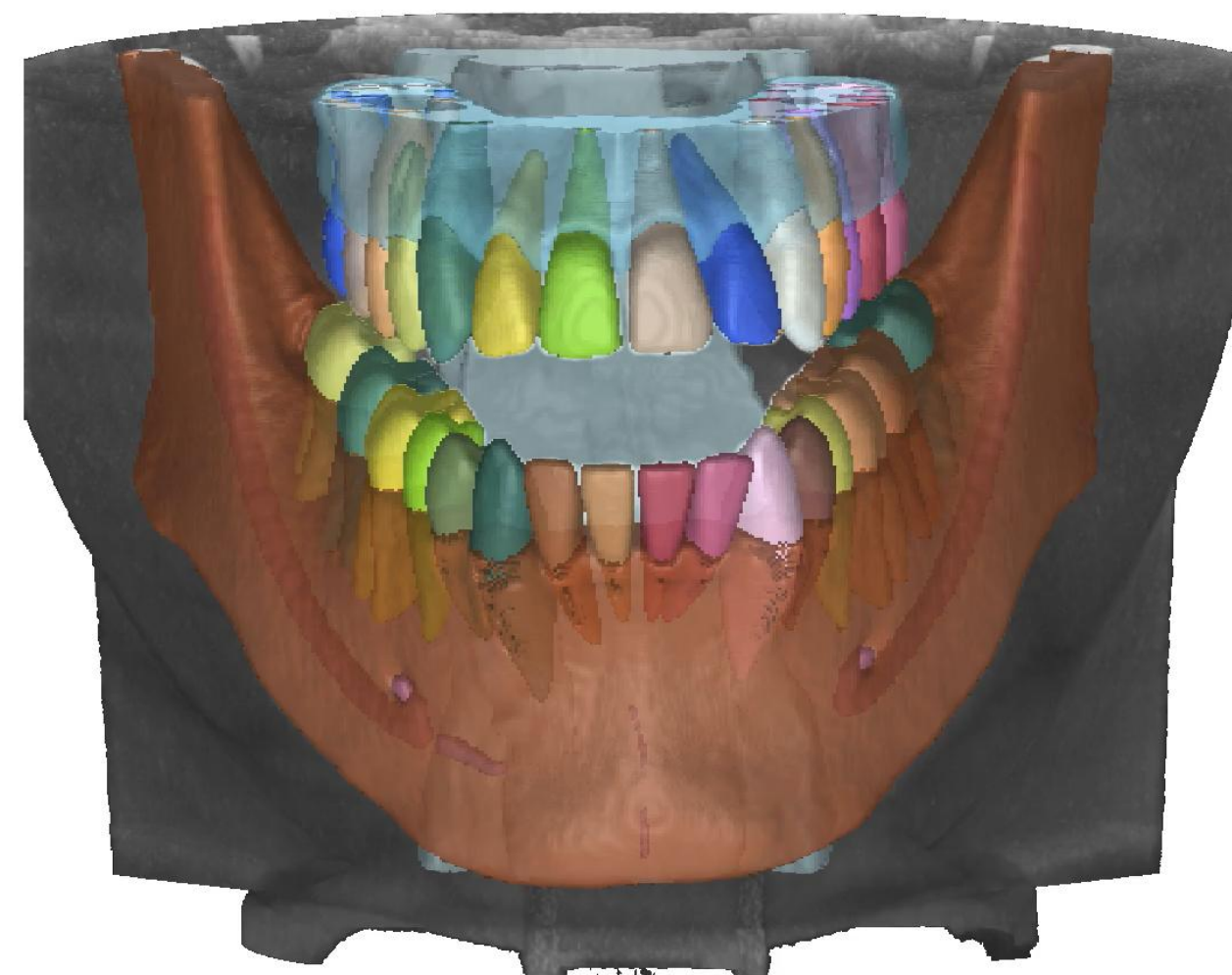
How far the AI contour strays from the expert annotation.

Lower is better.

Every structure in every scan is drawn by an expert. Best accuracy, highest cost.



INPUT: THE RAW SCAN



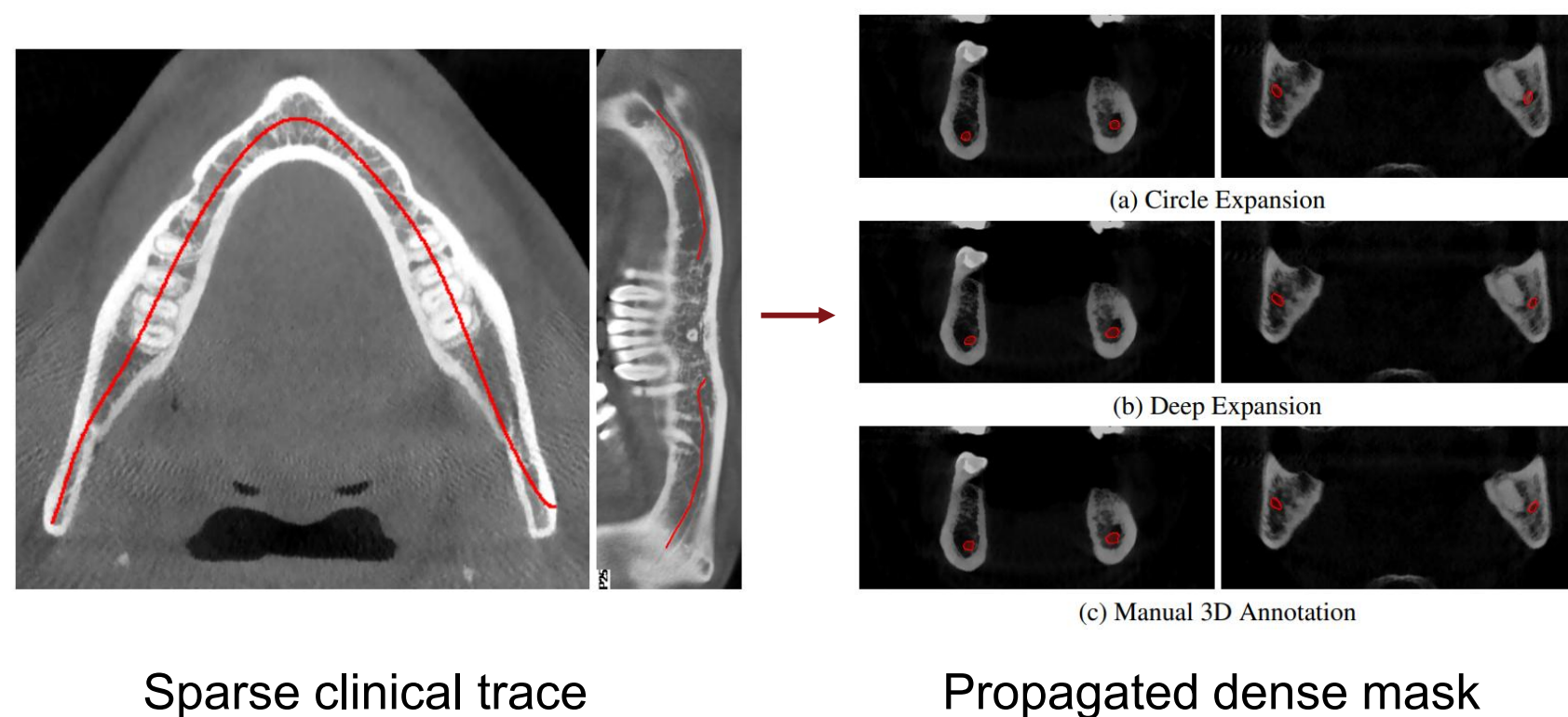
TARGET: DENSE EXPERT MASKS

Dense 3D masks are the exception. Sparse labels are what clinics already produce.

01

Transform the annotation the clinic already gives

Routine sparse labels, **propagated into dense 3D masks.**



[1] Cipriano M., et al. "Improving Segmentation of the Inferior Alveolar Nerve through Deep Label Propagation", CVPR 2022.

[2] Luo X., et al. "Scribble-Supervised Medical Image Segmentation via Dual-Branch Network and Dynamically Mixed Pseudo Labels Supervision", MICCAI 2022.

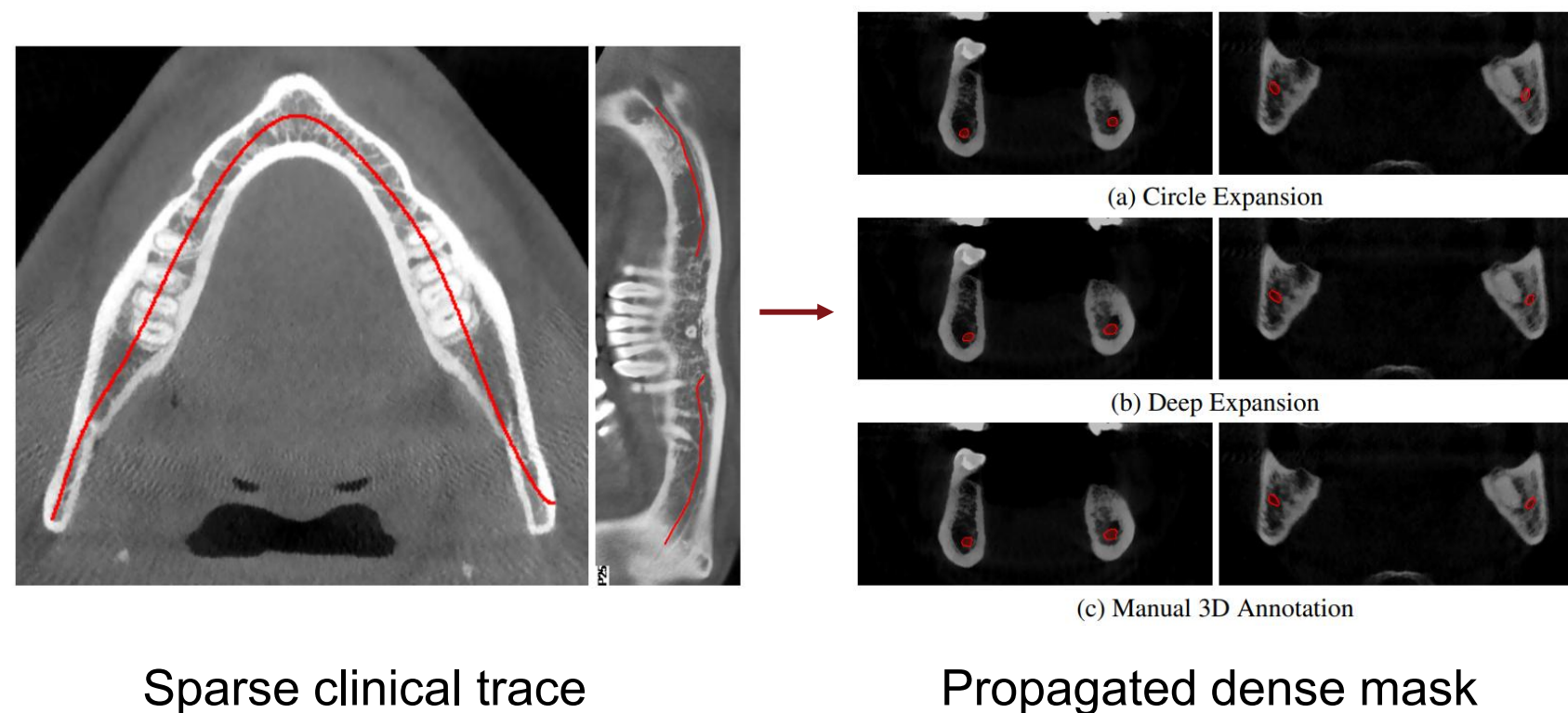
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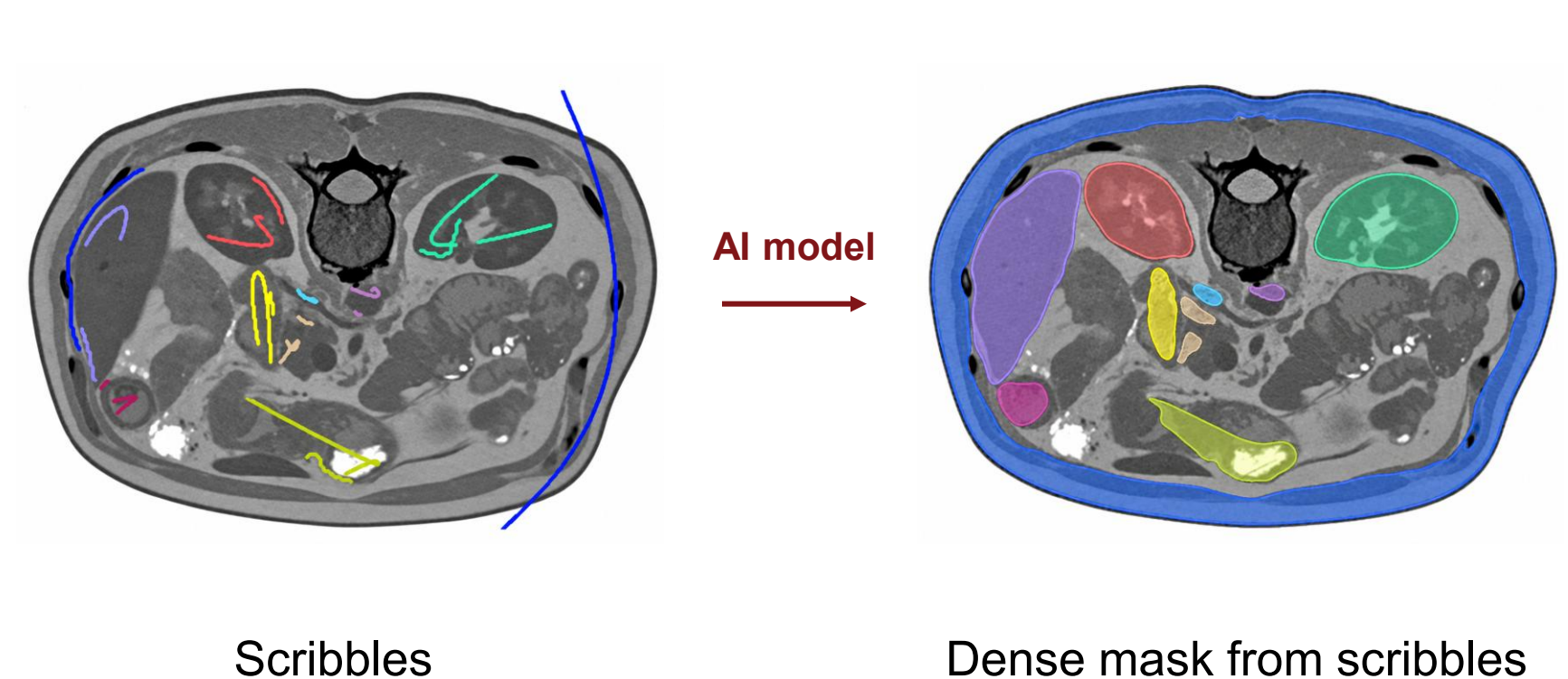
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02

Ask for less → Scribble annotation

A few clinician scribbles, **completed by a model.**

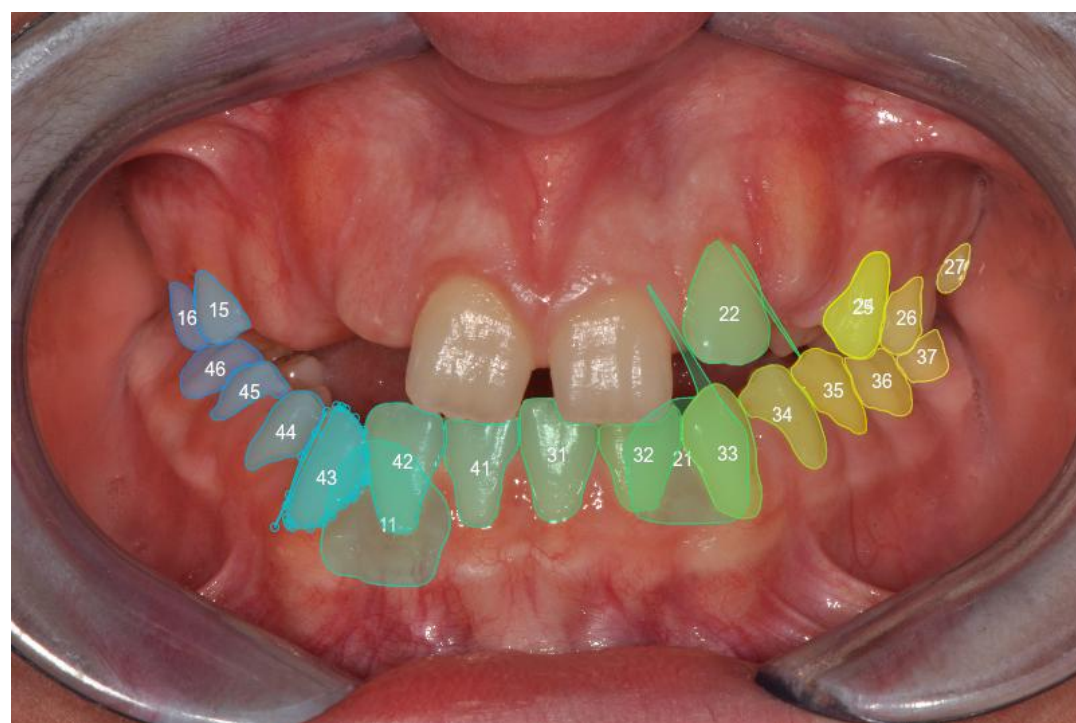


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The expert edits the AI's proposal instead of drawing from scratch.



01

AI proposes

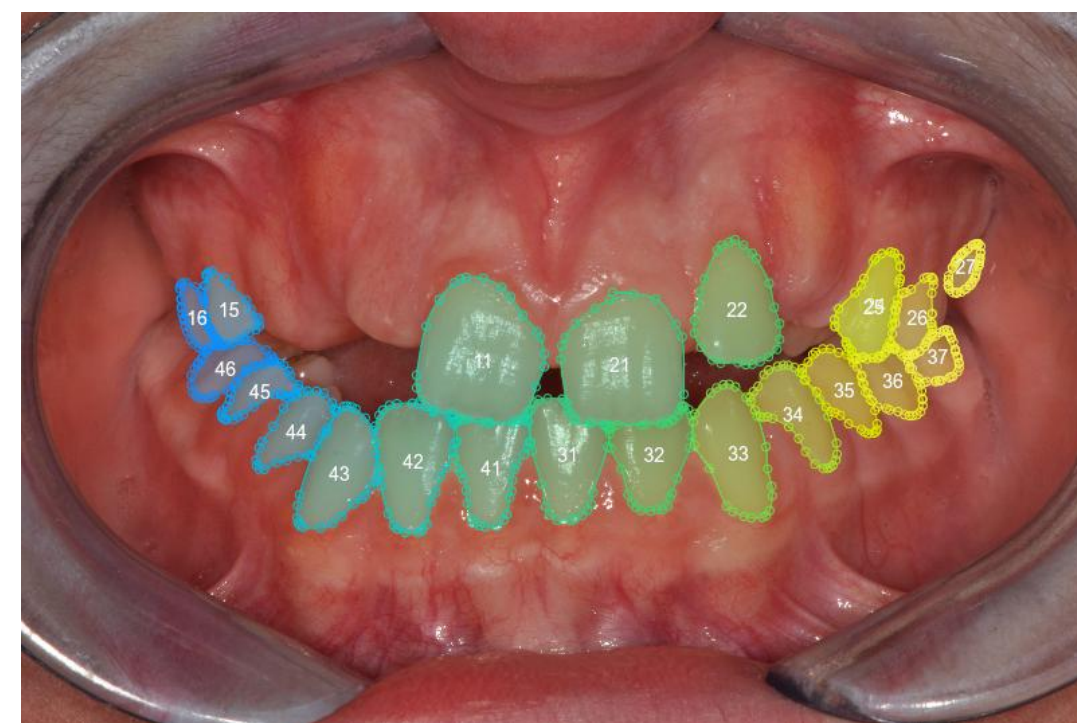
A first segmentation, in seconds.



02

Clinician corrects

A few clicks where the AI is wrong.



03

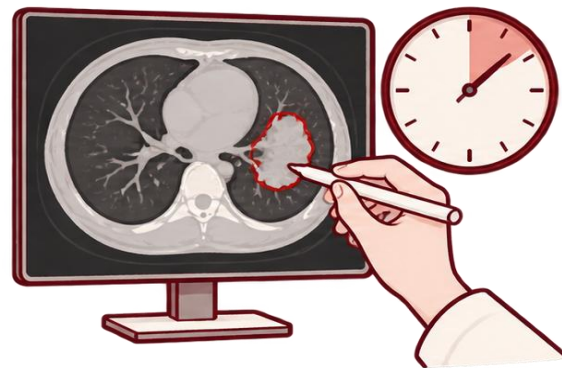
AI learns

Every correction becomes new training data.



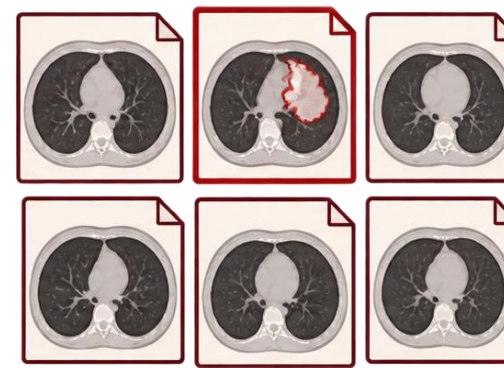
Models need more data than we can collect; **synthetic data can fill the gap.**

REAL DATA ONLY



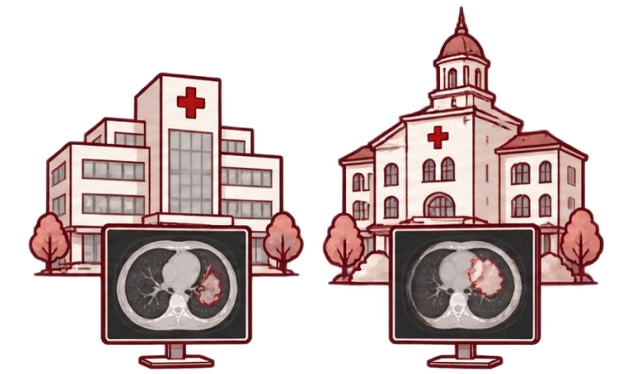
Scarcity of data

Every scan needs expert to annotate it, so **datasets stay small.**



Rare cases

Rare conditions appear in a handful of cases, so **models rarely see them.**

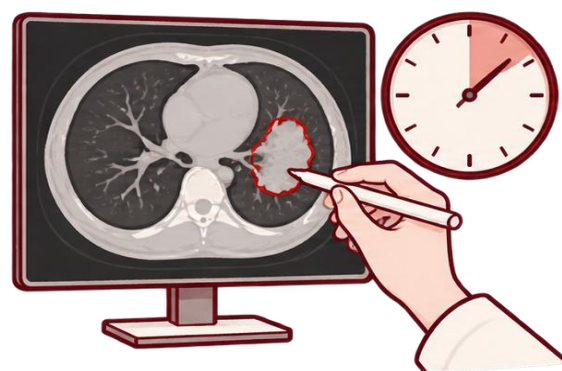


Limited data sharing

Privacy rules limit sharing, so **each center trains on its own data.**

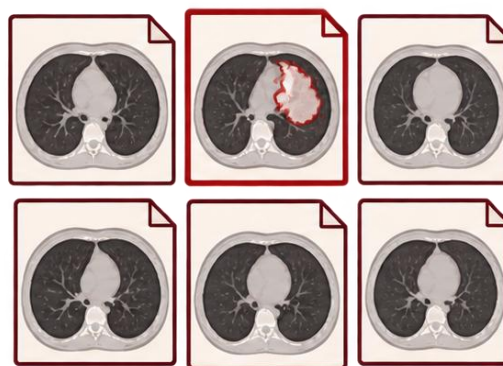
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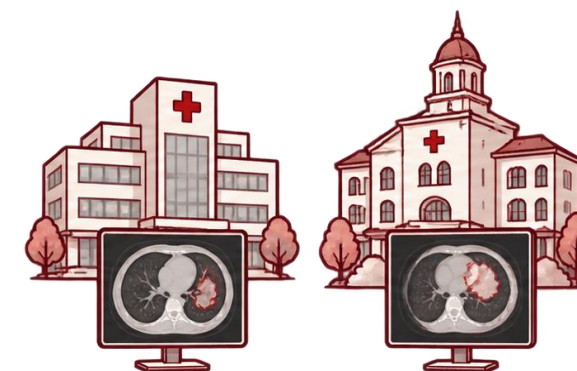
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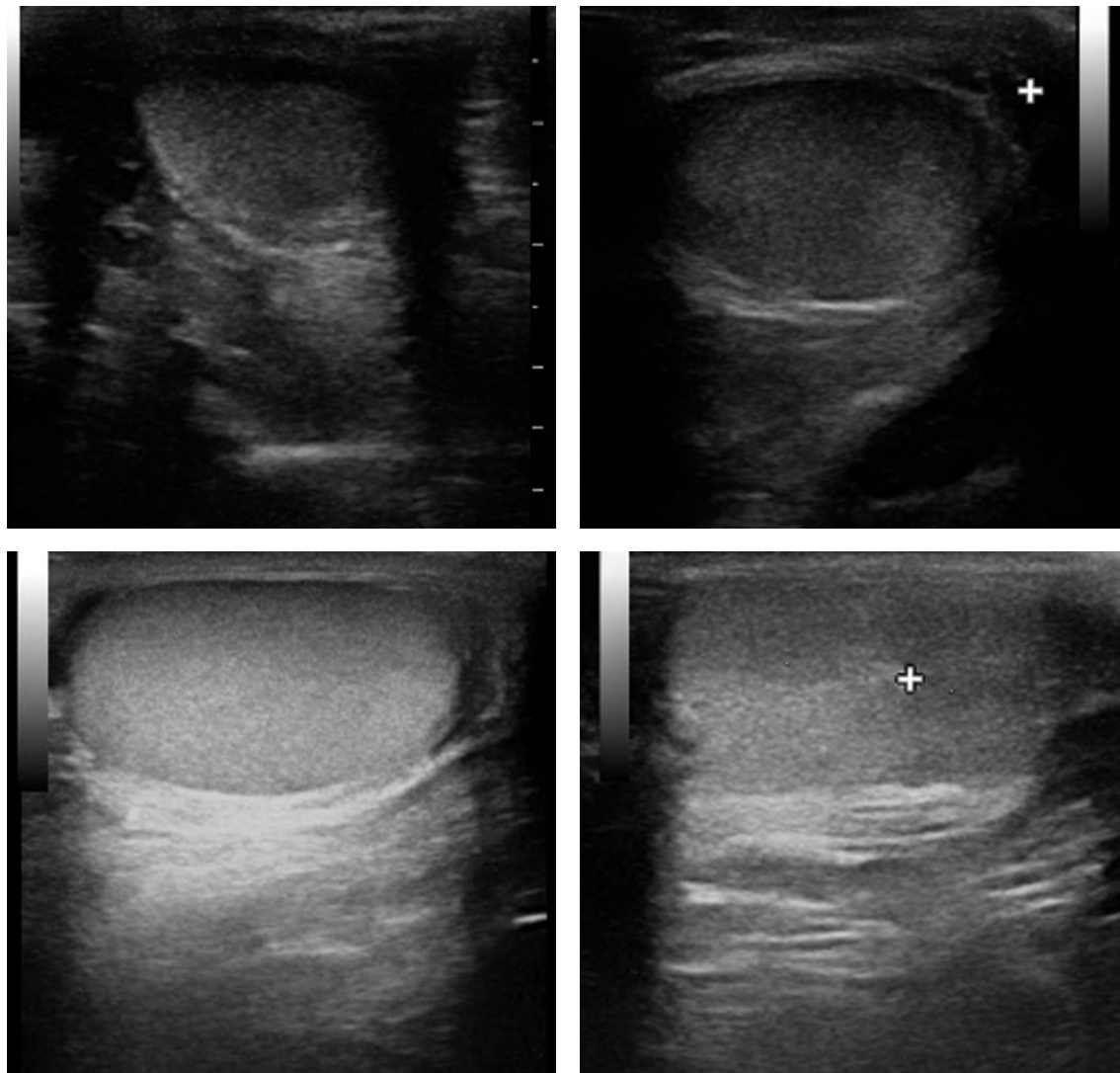
THE SYNTHETIC DATA SOLUTION

What is synthetic data?

Artificial scans created by an AI model: **realistic, but from no real patient.**

Where does it come from?

The generative model is **trained on real scans**: it learns from them, it does not totally replace them.



TESTICULAR ULTRASOUND

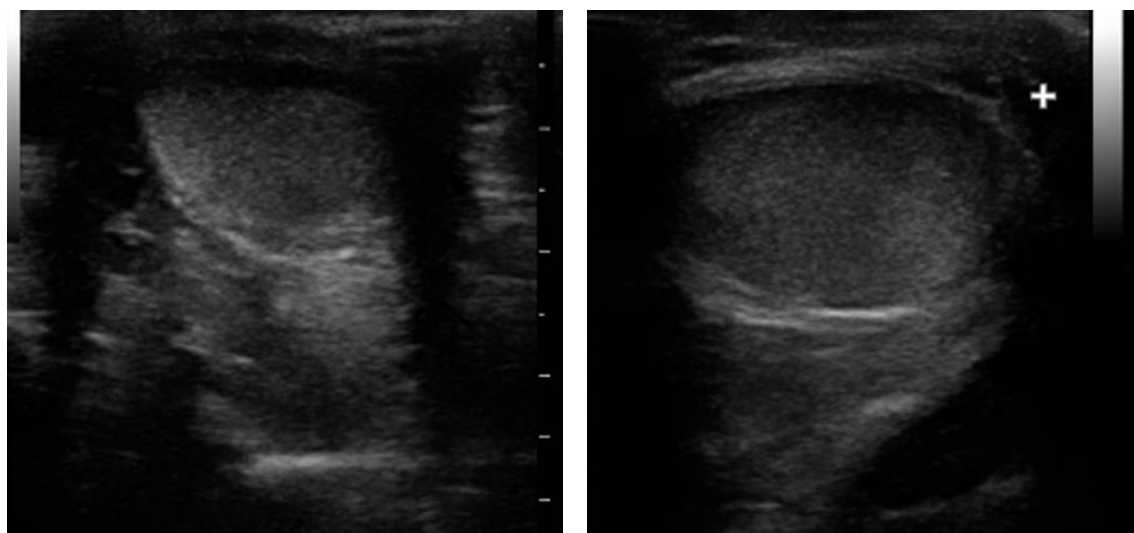
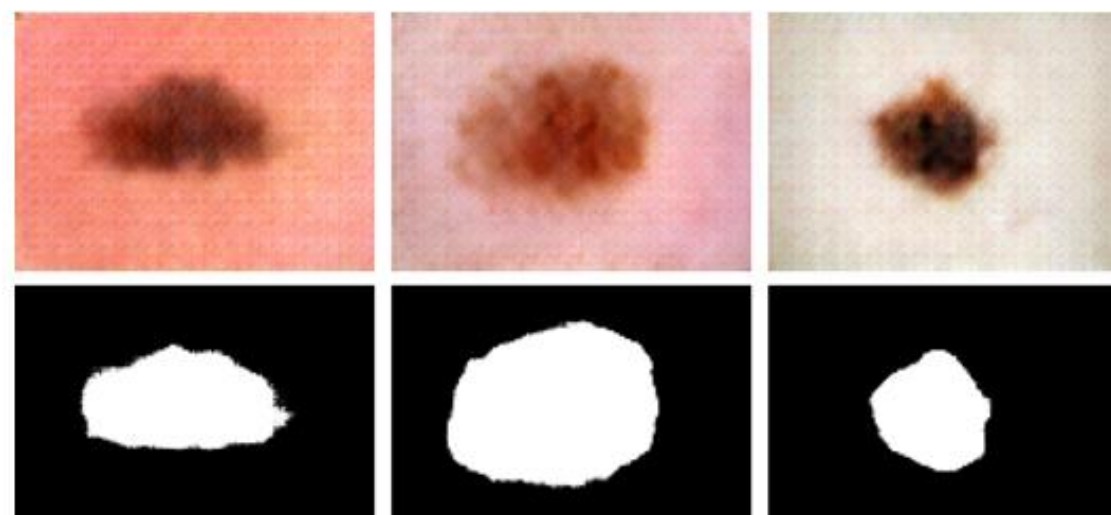
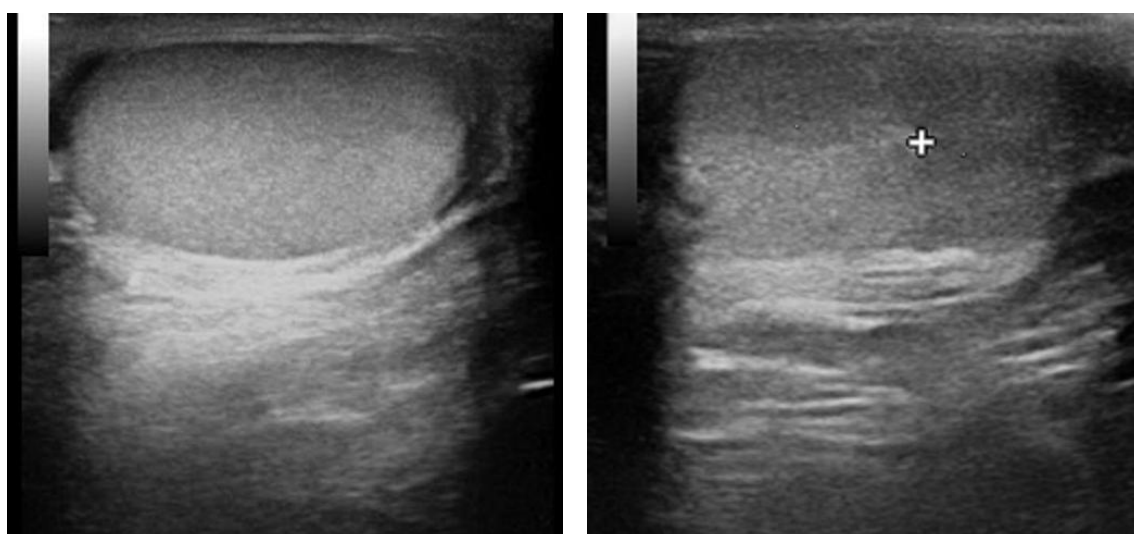
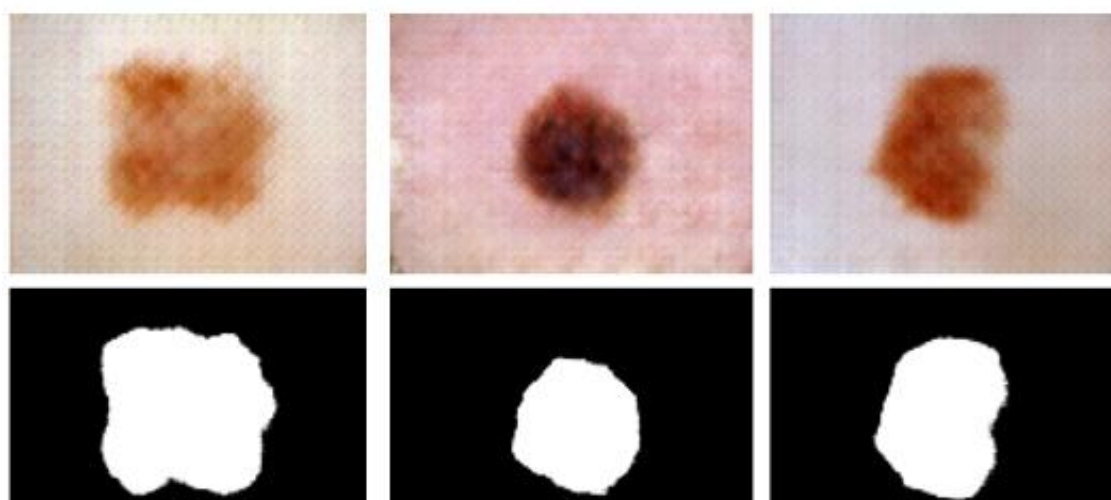
Synthetic pre-training matches real

A model pre-trained on synthetic scans performed about as well as one pre-trained on real scans.¹

[1] Morelli N., et al. "Enhancing Testicular Ultrasound Image Classification Through Synthetic Data and Pretraining Strategies", ICIAP 2025.

[2] Pollastri F., Bolelli F., et al. "Improving Skin Lesion Segmentation with Generative Adversarial Networks", CBMS 2018.

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SKIN LESIONS

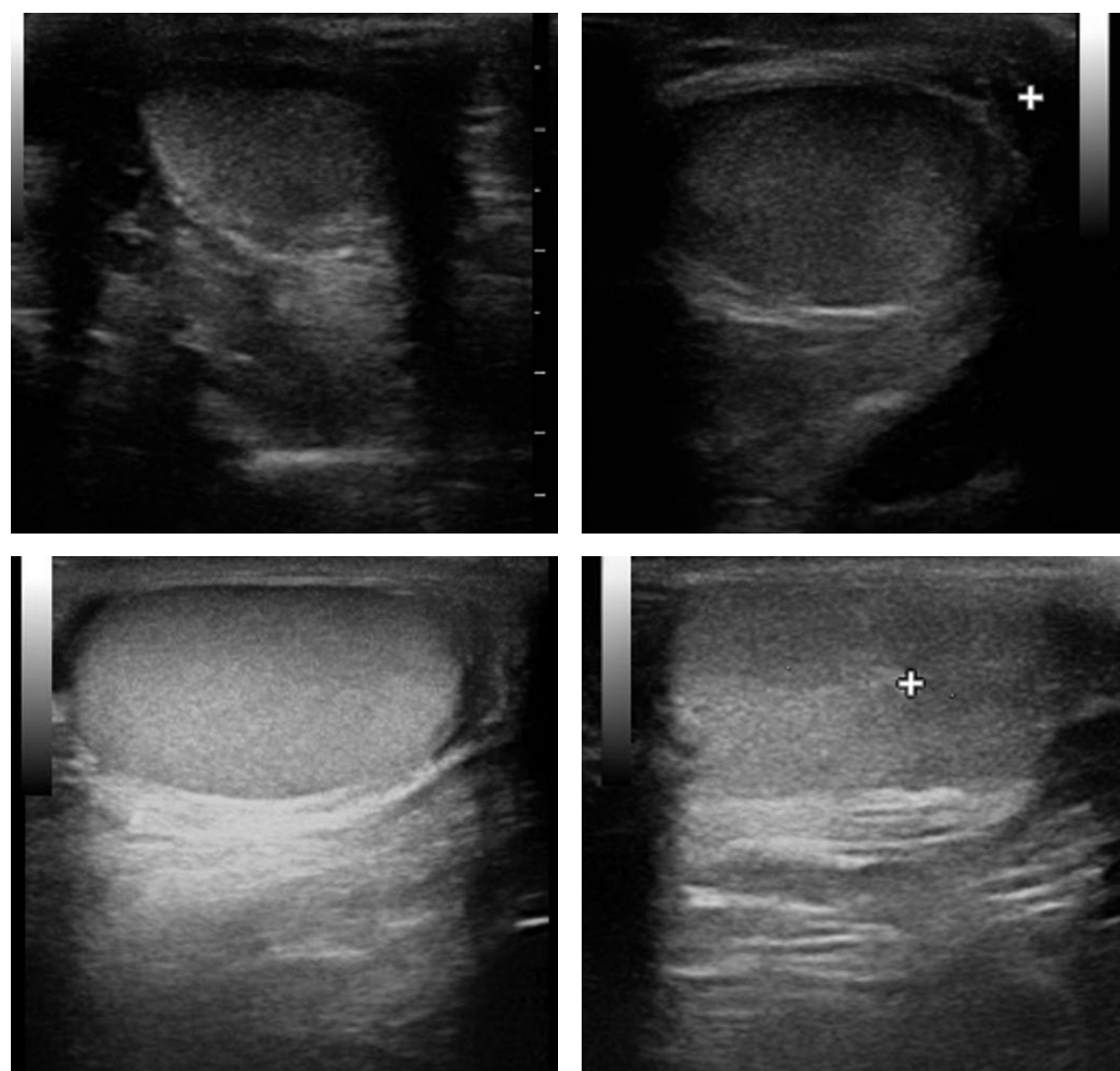
Every image comes with its mask

Synthetic lesion and mask pairs improved lesion segmentation.²

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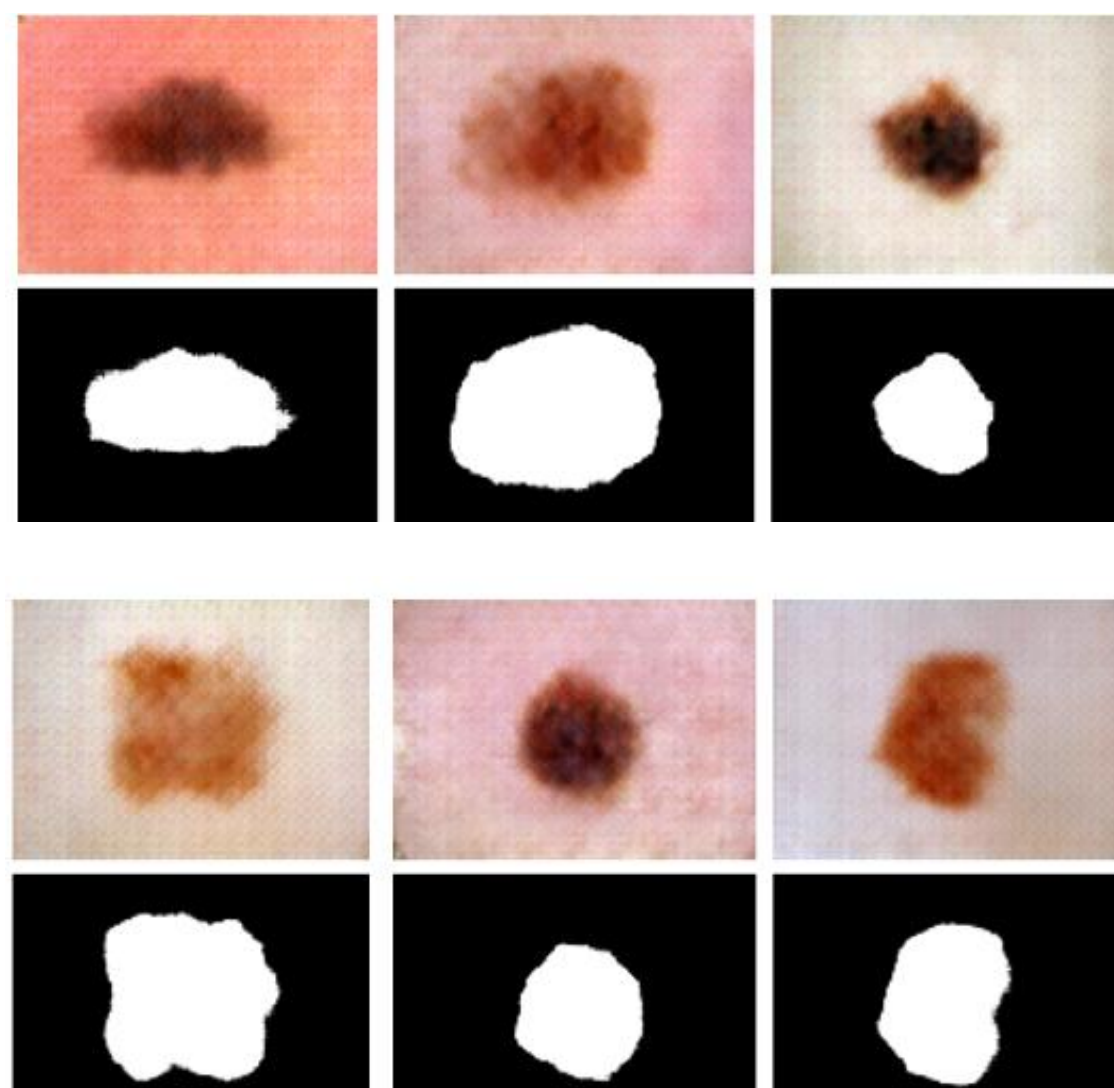
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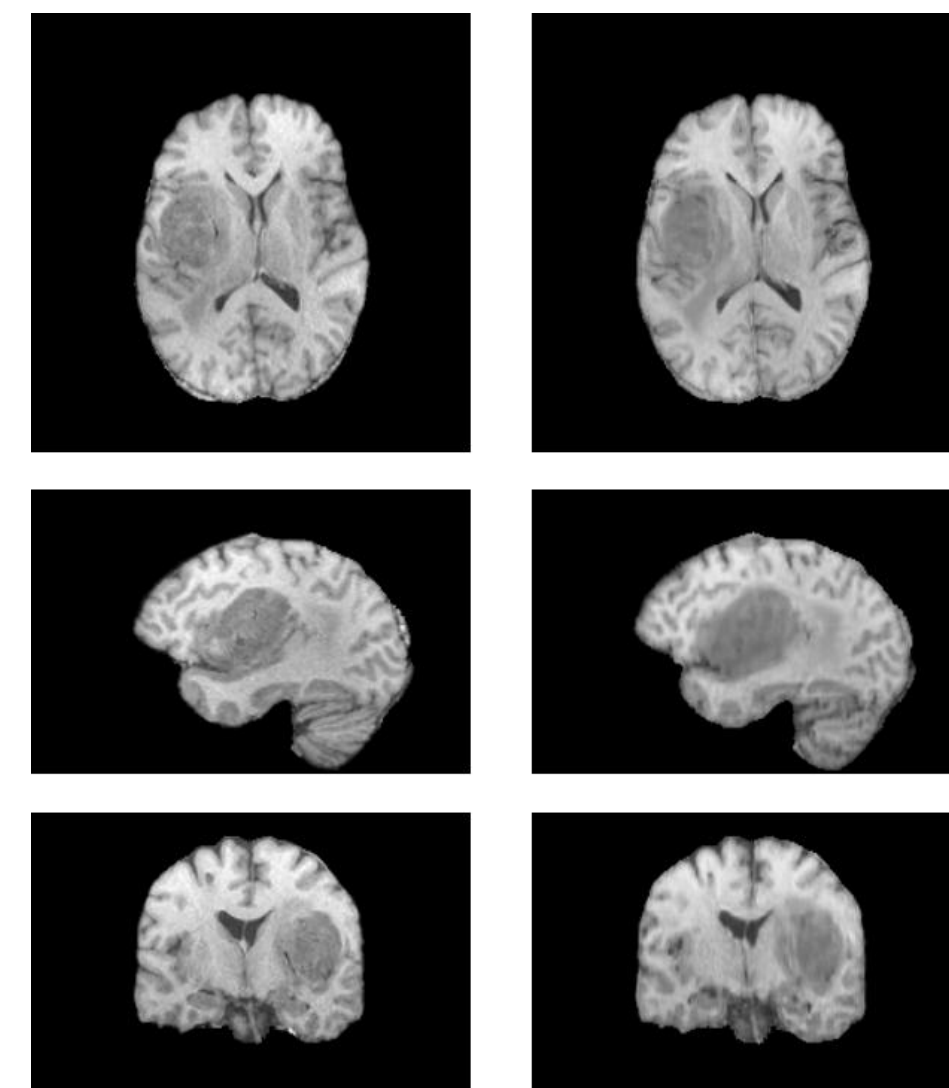
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SKIN LESIONS

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Synthetic lesion and mask pairs improved lesion segmentation.²



BRAIN MRI

Missing sequences, filled in

A missing MRI sequence is synthesized from the ones that were acquired.³

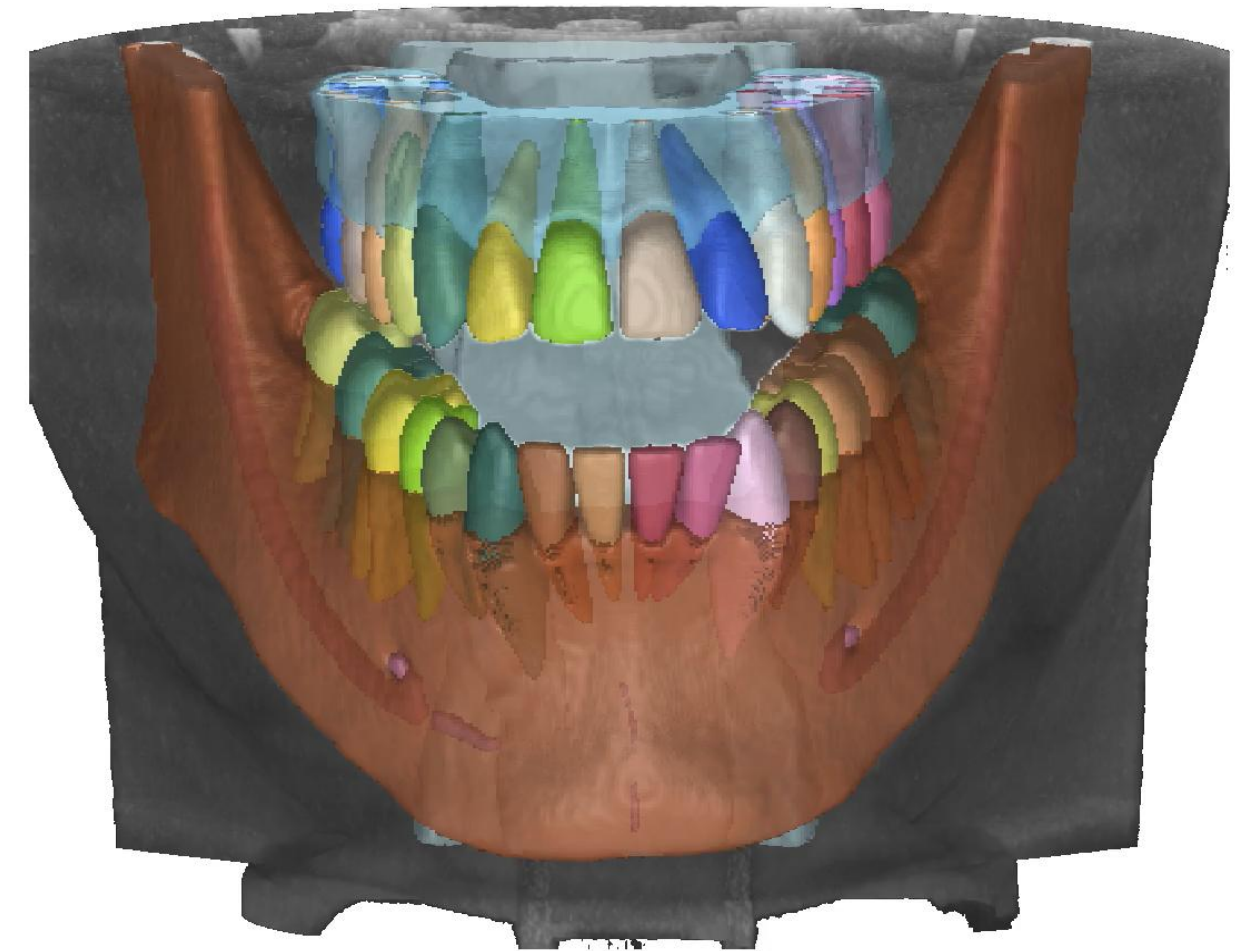
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Dental AI at AlmageLab

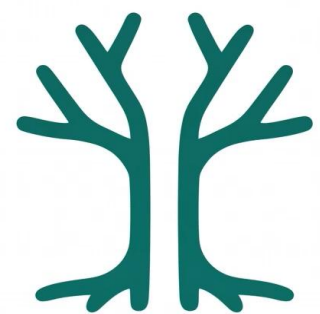
From the CBCT to the orthodontic patient.





Reducing annotation time does not solve annotation consistency.

- We moved the protocol itself into the infrastructure.
- Data are organized around the patient. Data can be visualized jointly, and the annotation protocol is encoded in the platform.
- Clinicians work collaboratively, instead of producing independent datasets that we later try to reconcile.



Yggdrasil

Multimodal clinical data and AI



ToothFairy: teams worldwide train AI on the same open data.

WHAT IS TOOTHFAIRY

Open dataset

CBCT scans with maxillo-facial structures annotated in 3D by clinicians, public for research.

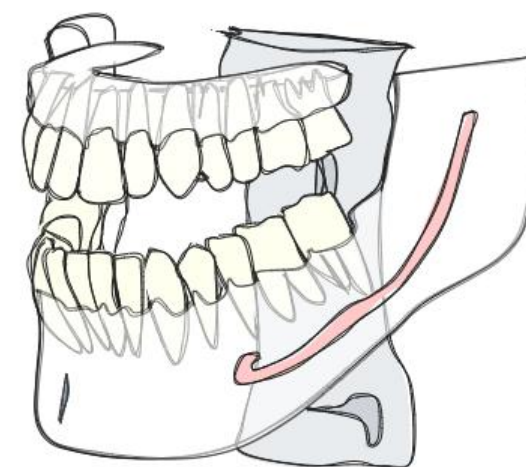
42 classes in ToothFairy2

Jaws, Inferior Alveolar Canals, Maxillary Sinus, Pharynx, Bridges, Crowns, Implants, and Teeth (also Wisdom Teeth)

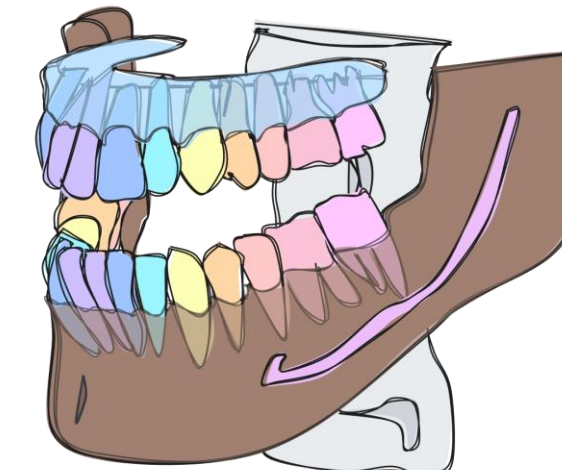
Hidden test set

An additional external test set, on which every team is scored on the same unseen cases.

THE FIRST TWO EDITIONS



2023

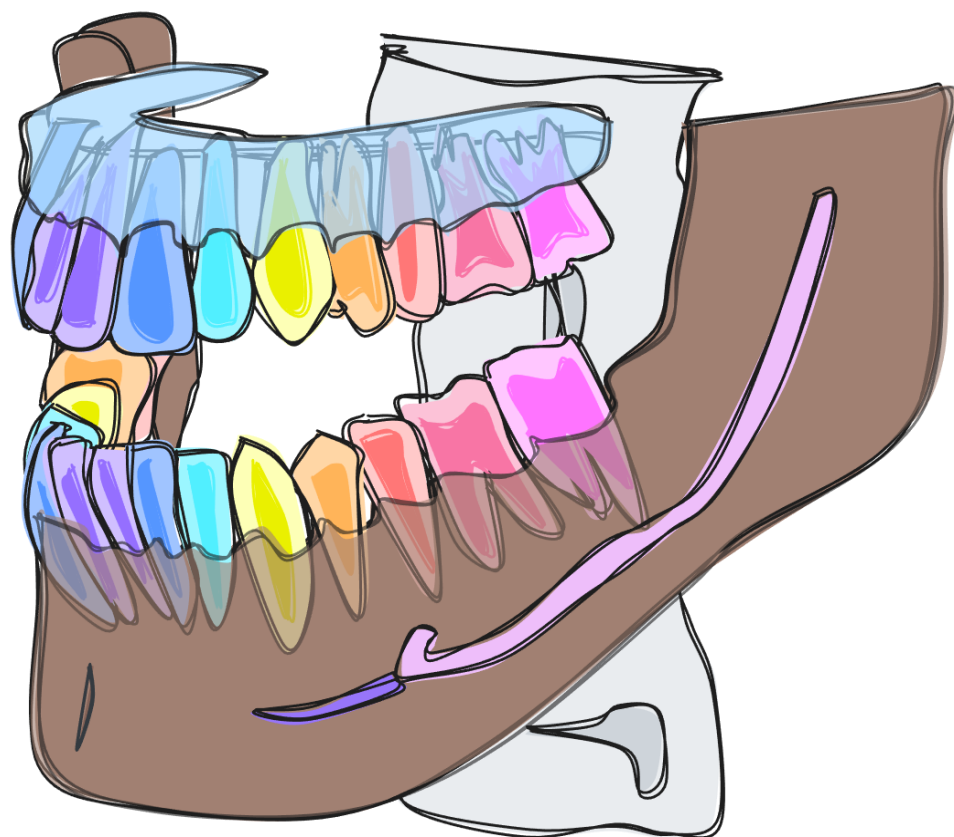


2024

[1] Bolelli F., et al. "Segmenting the Inferior Alveolar Canal in CBCT Volumes: The ToothFairy Challenge" IEEE Transactions on Medical Imaging 2024.

[2] Bolelli F., et al. "Multi-structure segmentation in CBCT volumes: The ToothFairy2 challenge." Medical Image Analysis 2026.

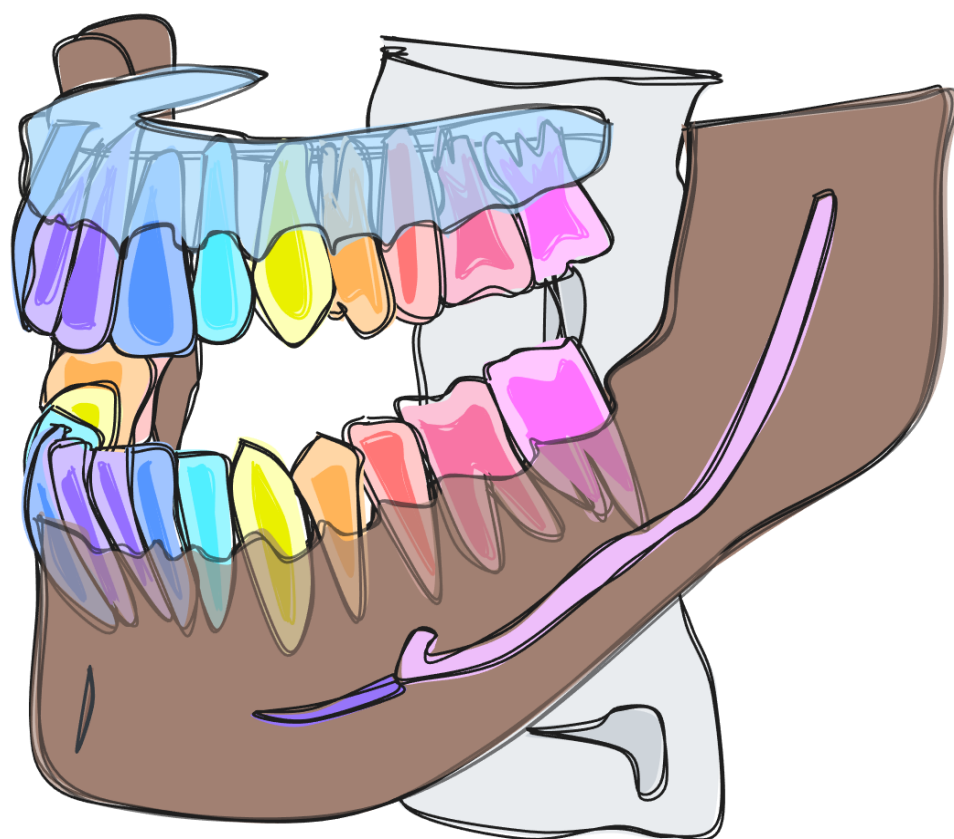
77 annotated structures in each scan. New classes: 32 dental pulps, lingual canal, incisive canals.



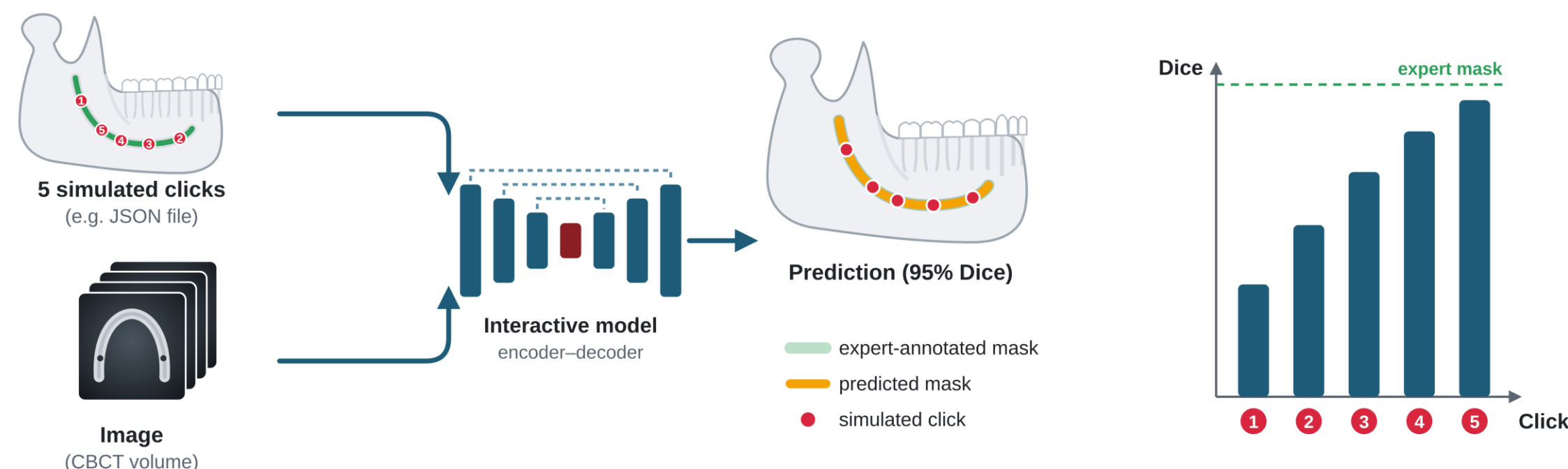
[1] Lumetti L., et al. "ToothFairy3: Scaling CBCT Maxillofacial Segmentation to 77 Classes with U-Mamba2." MICCAI 2026.

[2] Bolelli F., Lumetti L., et al. "ToothFairy3: Fast and Interactive Multi-class Segmentation in CBCT Volumes", MICCAI 2025 Challenge.

77 annotated structures in each scan. New classes: 32 dental pulps, lingual canal, incisive canals.



INTERACTIVE TRACK



TOOTH FAIRY3 2025
77 classes

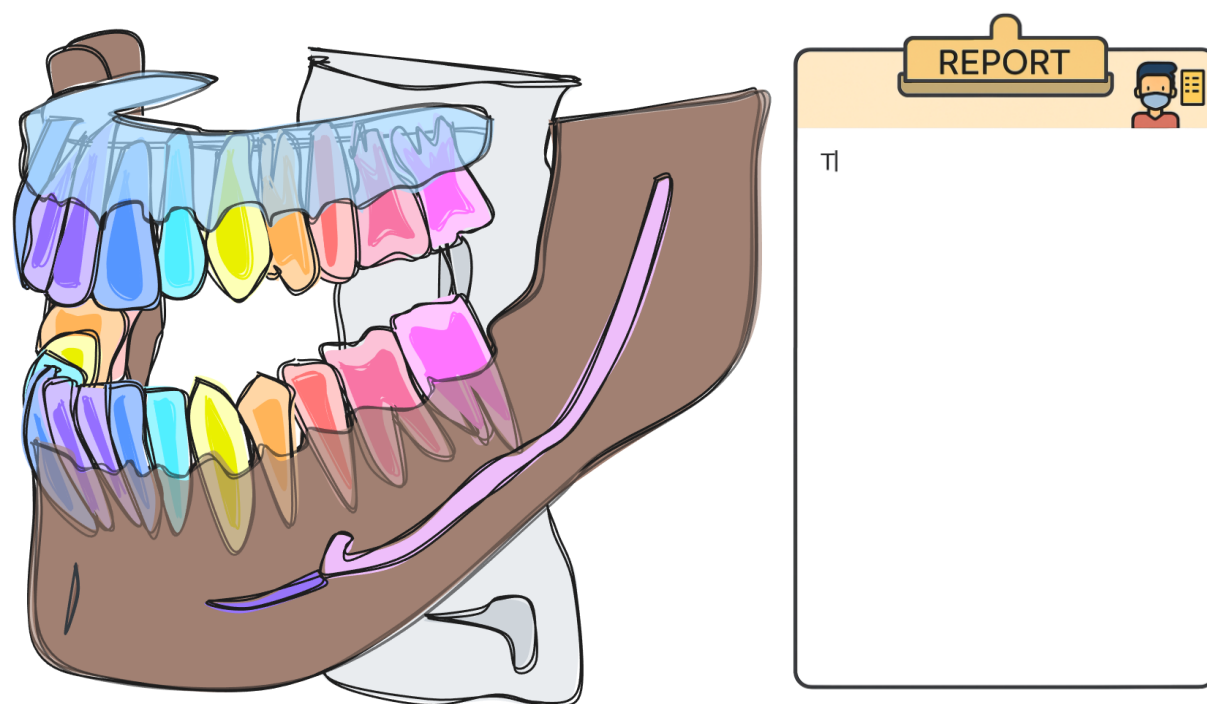
The clinician clicks where the mask is wrong and the AI corrects it at once. **Each click brings the predicted mask closer to the expert-annotated mask.**

[1] Lumetti L., et al. "ToothFairy3: Scaling CBCT Maxillofacial Segmentation to 77 Classes with U-Mamba2." MICCAI 2026.

[2] Bolelli F., Lumetti L., et al. "ToothFairy3: Fast and Interactive Multi-class Segmentation in CBCT Volumes", MICCAI 2025 Challenge.

From segmentation to reports. New datasets pair each scan with the clinician's report.

TOOTHFAIRY4 · 625 CBCTS



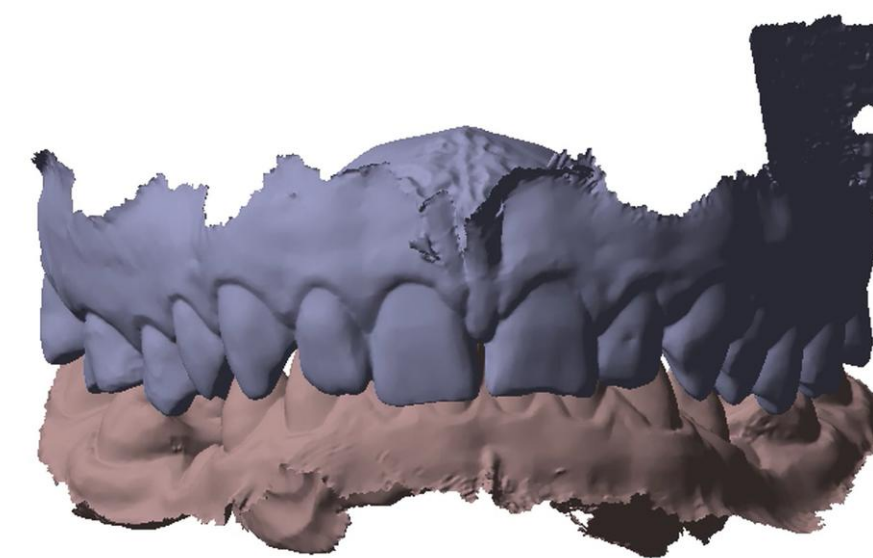
BITE2TEXT · 1,000 PATIENTS



Each patient: scan, photos and the orthodontist's written report.
New task: AI models that generate reports.



5 INTRAORAL PHOTOS



INTRAORAL SCANS

[1] Lumetti L., et al. "Ontology-Grounded Structured Prediction for Dental CBCT Reporting." MICCAI 2026.

[2] Lumetti L., Rizzo F., Cremonini F., et al. "Do Multimodal LLMs Understand Intraoral Dental Data? Dataset, Platform, and Baselines", ECCV 2026.

Word-overlap metrics can score a report highly while it gets **the diagnosis wrong**.

REF	Teeth	18,	28,	38,	48	are	absent
GENERATED	Teeth	18,	28,	38,	48	are	endodontically treated
6 of 7 tokens identical → high n-gram overlap							the one token that carries the diagnosis
0.68 BLEU-4				0.00 FINDING AGREEMENT			
reads as a strong match				wrong diagnosis!			

WHY THEY FAIL

Count shared words

6 of 7 tokens match, so the score is high.

Ignore meaning

“Absent” vs “treated” flips the finding, not the score.

Punish rewording

“No caries” and “caries-free” share no words.

Reports need a metric that checks the **findings**, not the words.



Competitions

Choose an active competition to vote or review its ranking.

ACTIVE EVALUATION

B2T testset LMArena

Competition to decide the winner of the Bite2Text Challenge

[Intraoral photos](#)

[IOS scans](#)

[Start voting →](#)

[View leaderboard](#)

ACTIVE EVALUATION

TF4 testset LMArena

Competition to decide the winner of the Toothfairy4 Challenge

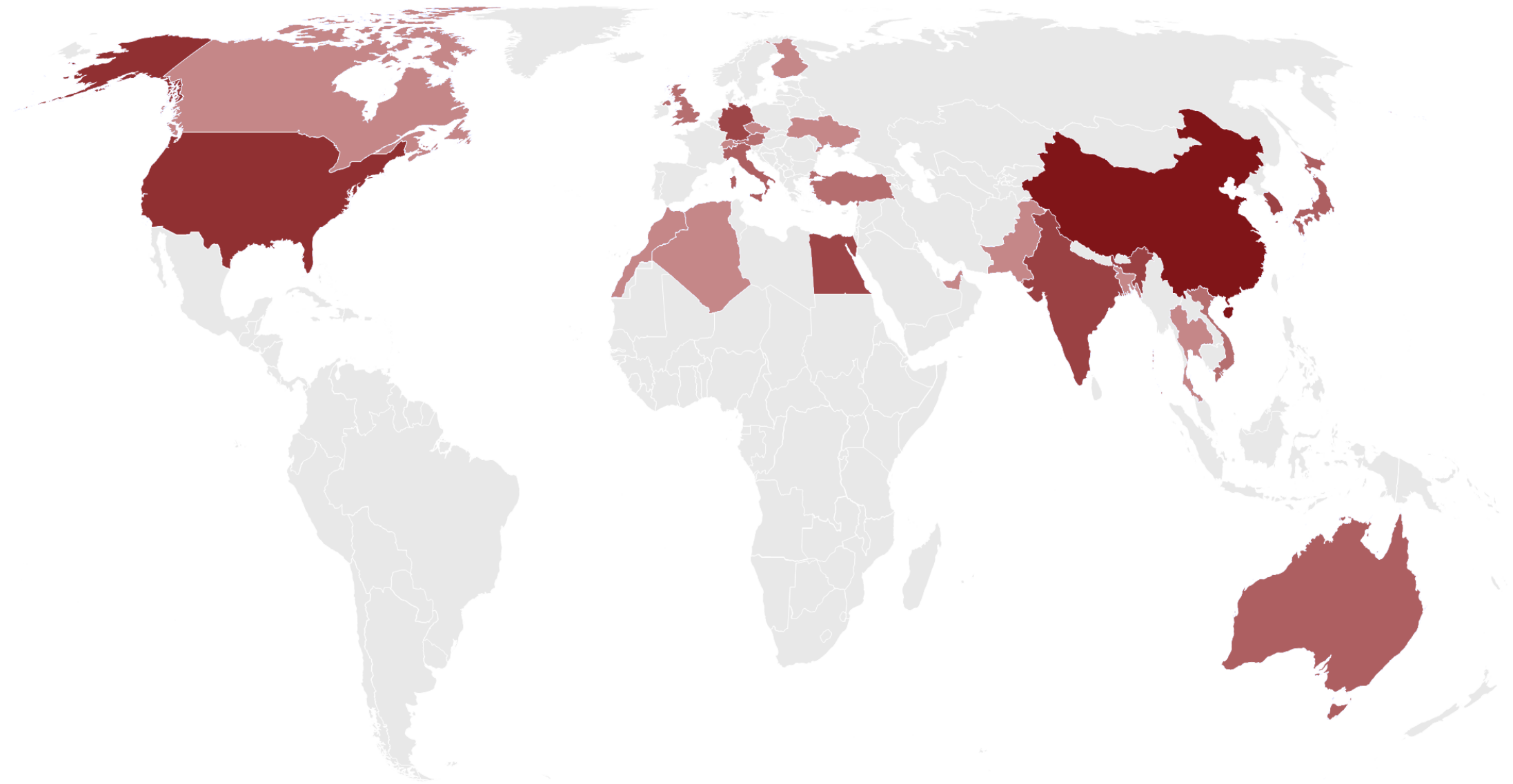
[CBCT](#)

[Panoramic](#)

[Start voting →](#)

[View leaderboard](#)

ODIN 2026 · MICCAI · STRASBOURG



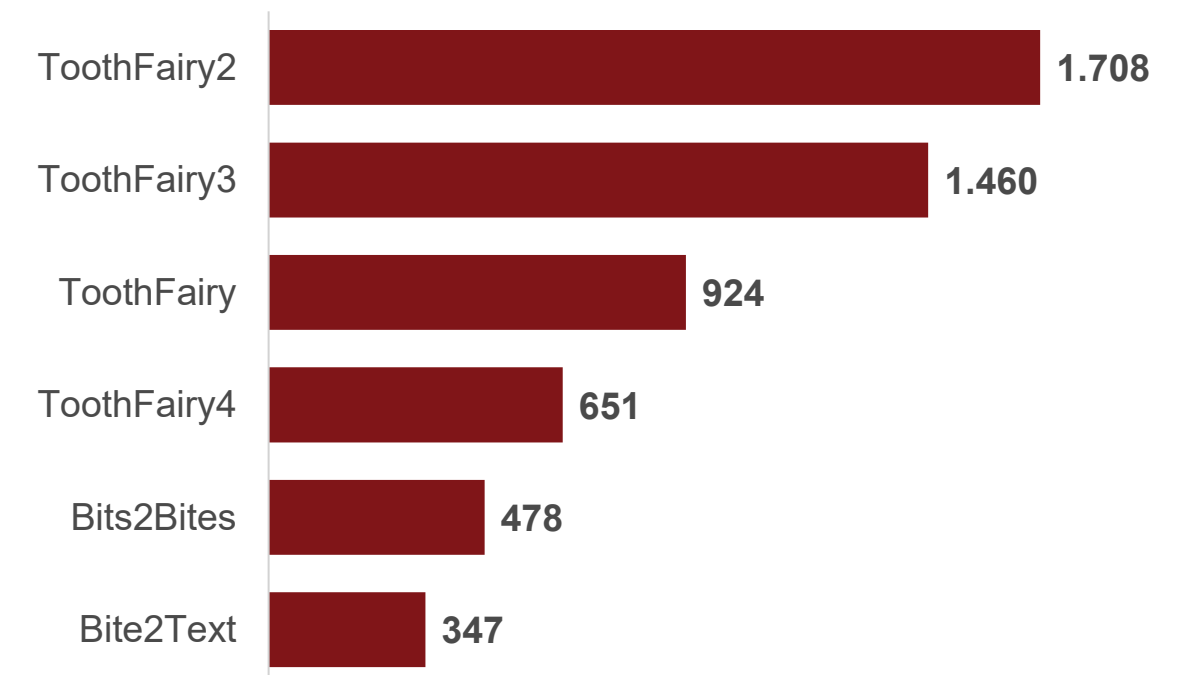
114 participants across 24 countries in the 2026 edition

1,195

participants over 4 editions, 2023 → 2026

5,568

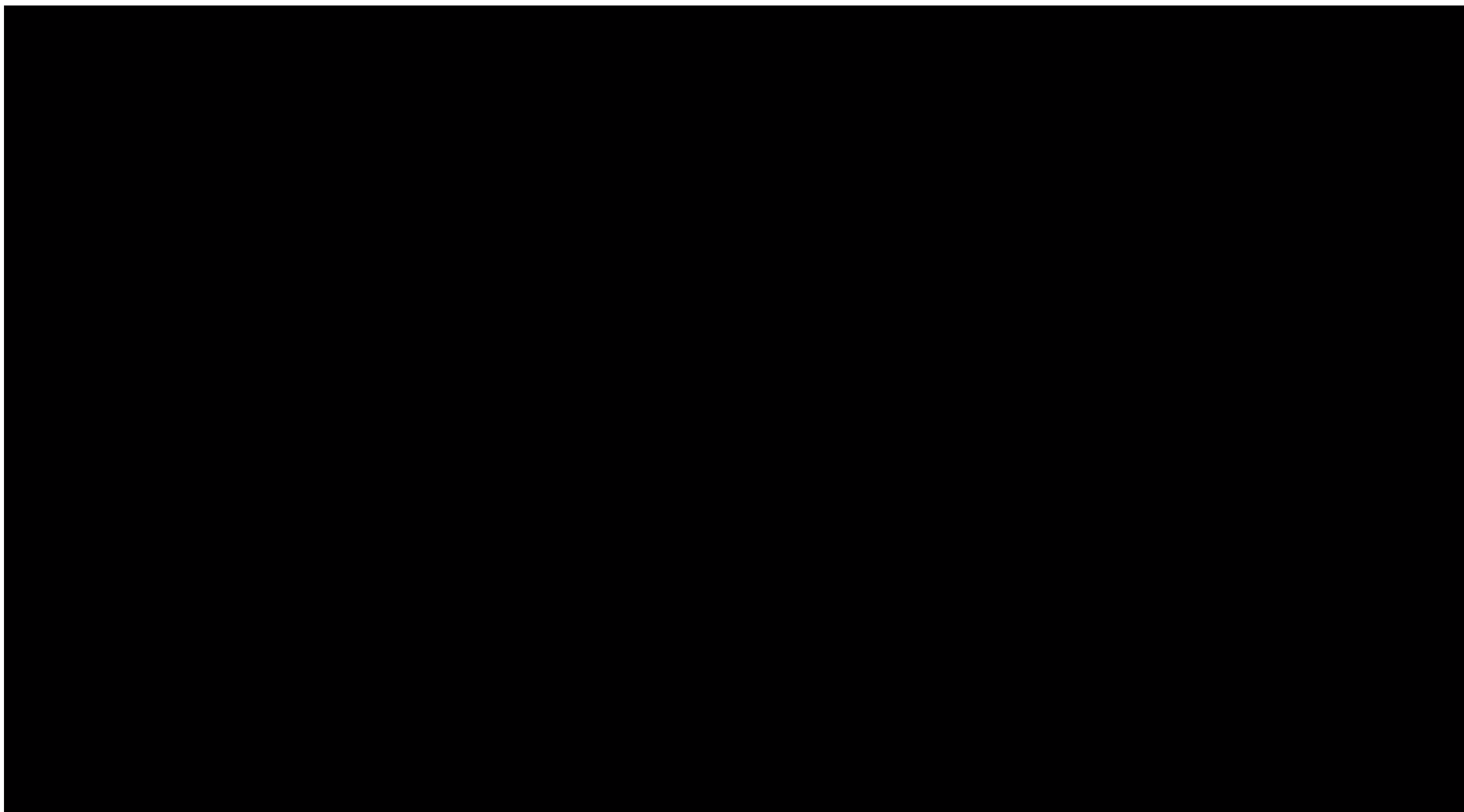
dataset downloads, 2023 → 2026



[1] Bolelli F., et al. "Segmenting the Inferior Alveolar Canal in CBCT Volumes: The ToothFairy Challenge" IEEE TMI 2024.

[2] Bolelli F., et al. "Multi-structure segmentation in CBCT volumes: The ToothFairy2 challenge." Medical Image Analysis 2026.

Source: Grand Challenge statistics pages (participants; ODIN 2026 from organizers); AlmageLab Datasets, ditto.ing.unimore.it (downloads), Oct 2026.



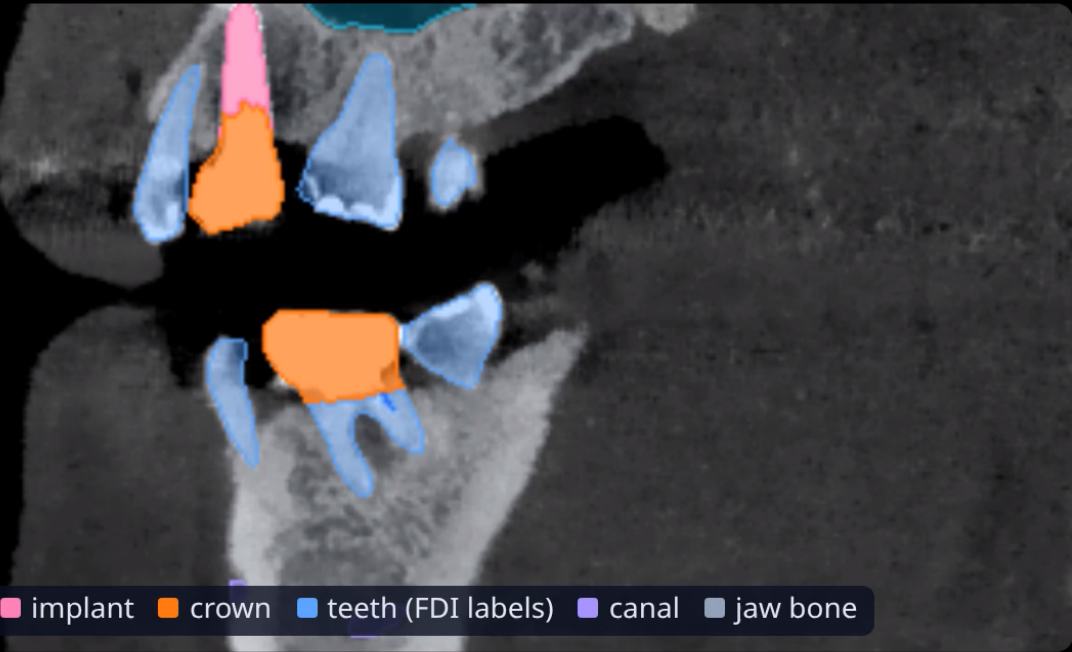
[1] Lumetti L., et al. "Ontology-Grounded Structured Prediction for Dental CBCT Reporting", MICCAI 2026.

[2] Saporita A., Pipoli V., et al. "PATHOCLASS-BRCA: Reframing PathologyReport Generation as Guideline-Aligned Multi-Task Classification", BMVC 2026

■ CBCT SCAN cbct/volume.nii.gz



■ SEGMENTATION MASK mask/mask.nii.gz



■ RADIOLOGY REPORTS reports_en/ · two independent readings of the same scan

■ **Report 1** reports_en/cbct_14_397.txt

Mandible:

Right mandibular canal with a regular course.

Left mandibular canal with a regular course.

Tooth 36 endodontically treated.

Absence of tooth 46.

No definite osteolytic or osteocondensing lesions.

Maxilla:

Maxilla partially included in the acquisition.

Presence of endosseous implants in positions 16 and 25, on which prosthetic reconstruction has already been performed.

Mandibular condyles:

Excluded from the acquisition and not visible.

■ **Report 2** reports_en/cbct_27_1707.txt

MANDIBLE included in the scan volume. Right and left mandibular canals with a regular course, predominantly lingual. Extruded lower third molars. Missing tooth 46. Endodontic treatment of tooth 36 with prosthetic crown and likely mini post-and-core. Likely conservative dental treatment involving teeth 48-37. Carious process involving 48-47-35-37. Radiopaque lesion in continuity with the cortical bone in the right molar region.

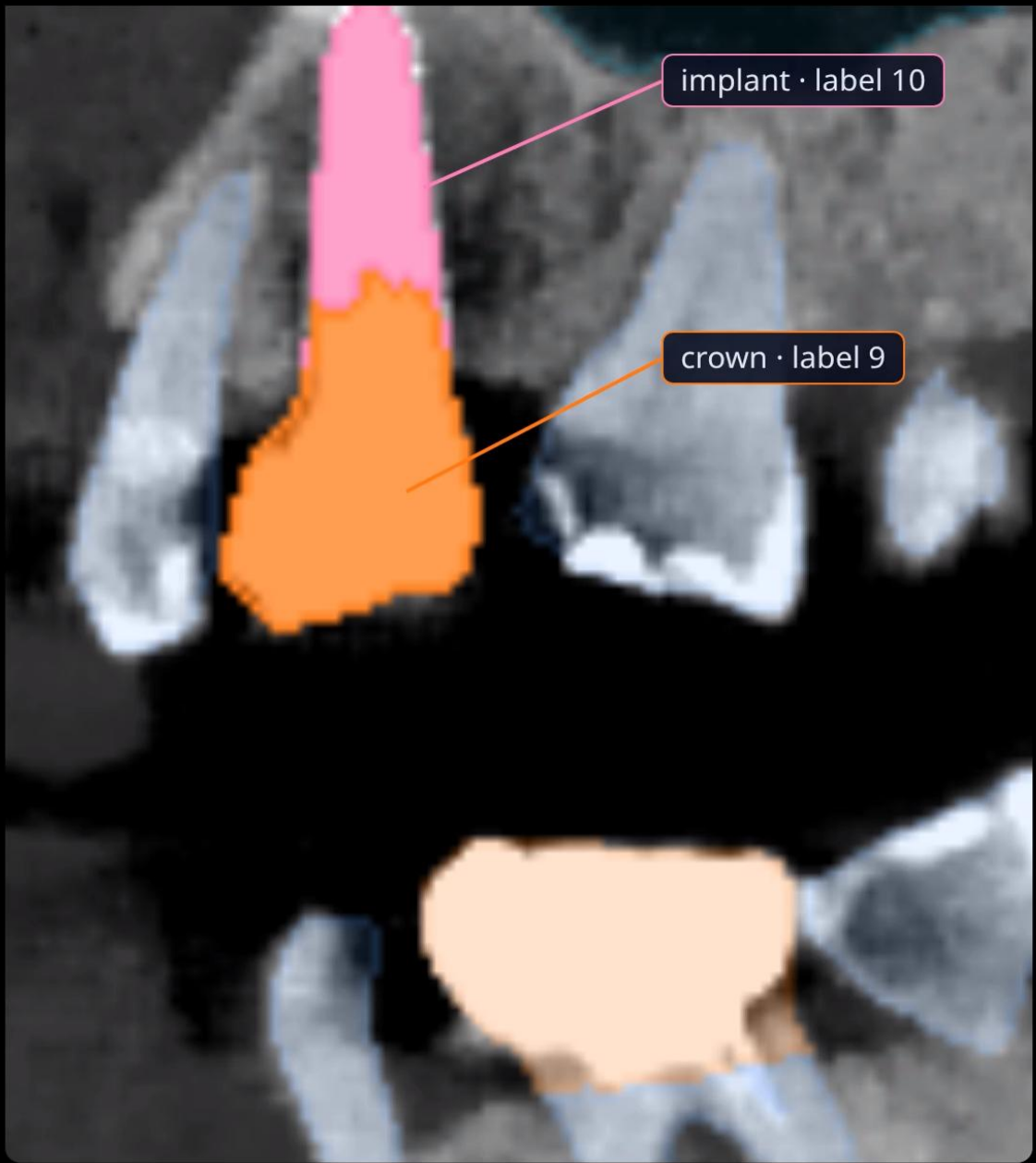
MAXILLA partially included in the scan volume. Missing 18, 16-25-28.

Implant-prosthetic rehabilitation of teeth 16-25. Carious processes involving 17-24-26-27 (presence of numerous artifacts; the presence in additional teeth cannot be excluded). Conservative dental treatment involving 27-26 (presence of numerous artifacts; the presence in additional teeth cannot be excluded). Reflective dental material in the incisor region (for orthodontic treatment?).

MAXILLARY SINUSES minimally included in the scan volume.

MANDIBULAR CONDYLES not included in the scan volume.

■ SEGMENTATION MASK mask/mask.nii.gz



parser/mask_parser.py: splits the restoration labels into connected components; the implant takes the nearest absent tooth slot, the crown sits on the implant it touches

■ REPORT SENTENCES

■ report 1 · cbct_14_397.txt

“Presence of endosseous implants in positions 16 and **25**, on which prosthetic reconstruction has already been performed.”

■ report 2 · cbct_27_1707.txt

“Missing 18, 16-**25**-28.”

■ report 2 · cbct_27_1707.txt

“Implant-prosthetic rehabilitation of teeth 16-**25**.”

parser/split_reports.py, report_parser.py: an LLM splits each report into findings, keeping each one's sentence verbatim, then types each finding

■ FACTS ABOUT IMPLANT 25

◆ Implant in tooth slot 25

■ mask · label 10

■ report 1

■ report 2

◆ Crown on that implant

■ mask · label 9

■ report 1

◆ Tooth 25 absent

no tooth labelled 25 in the mask either

■ report 1

■ report 2

◆ Implant: 83.8 mm³ at voxel (281.1, 314.4, 226.4)

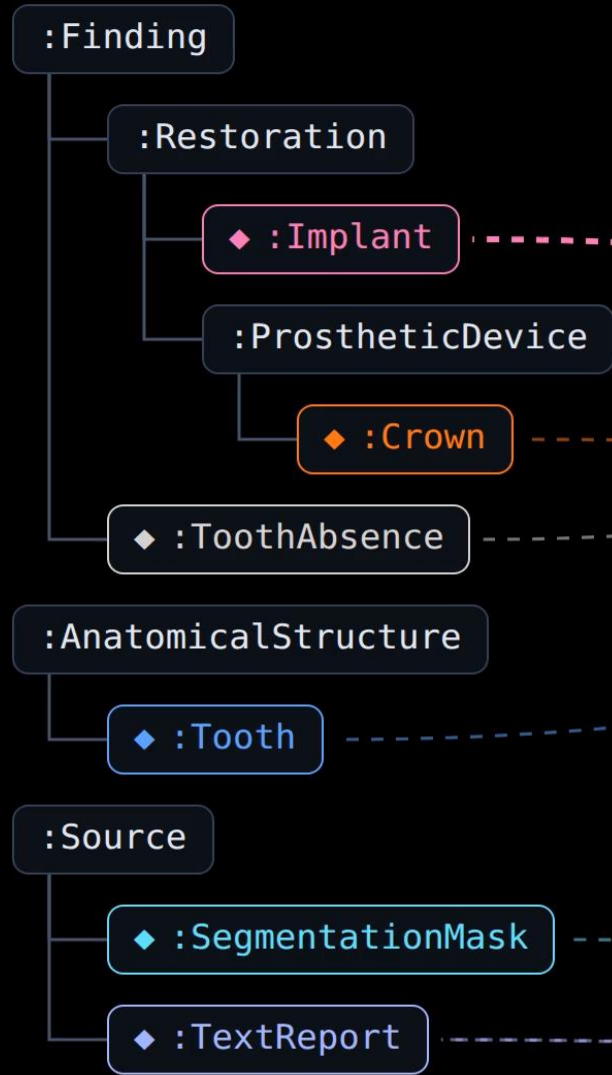
■ mask

■ Scan: 0.3 mm voxels, orientation LAS

■ CBCT image header

ONTOLOGY `ontology/ontology.ttl`

Reusable classes, each under its superclass, and properties: the same for every case



`:replacesTooth` `Finding` → `Tooth`, a sub-property of `:aboutStructure`

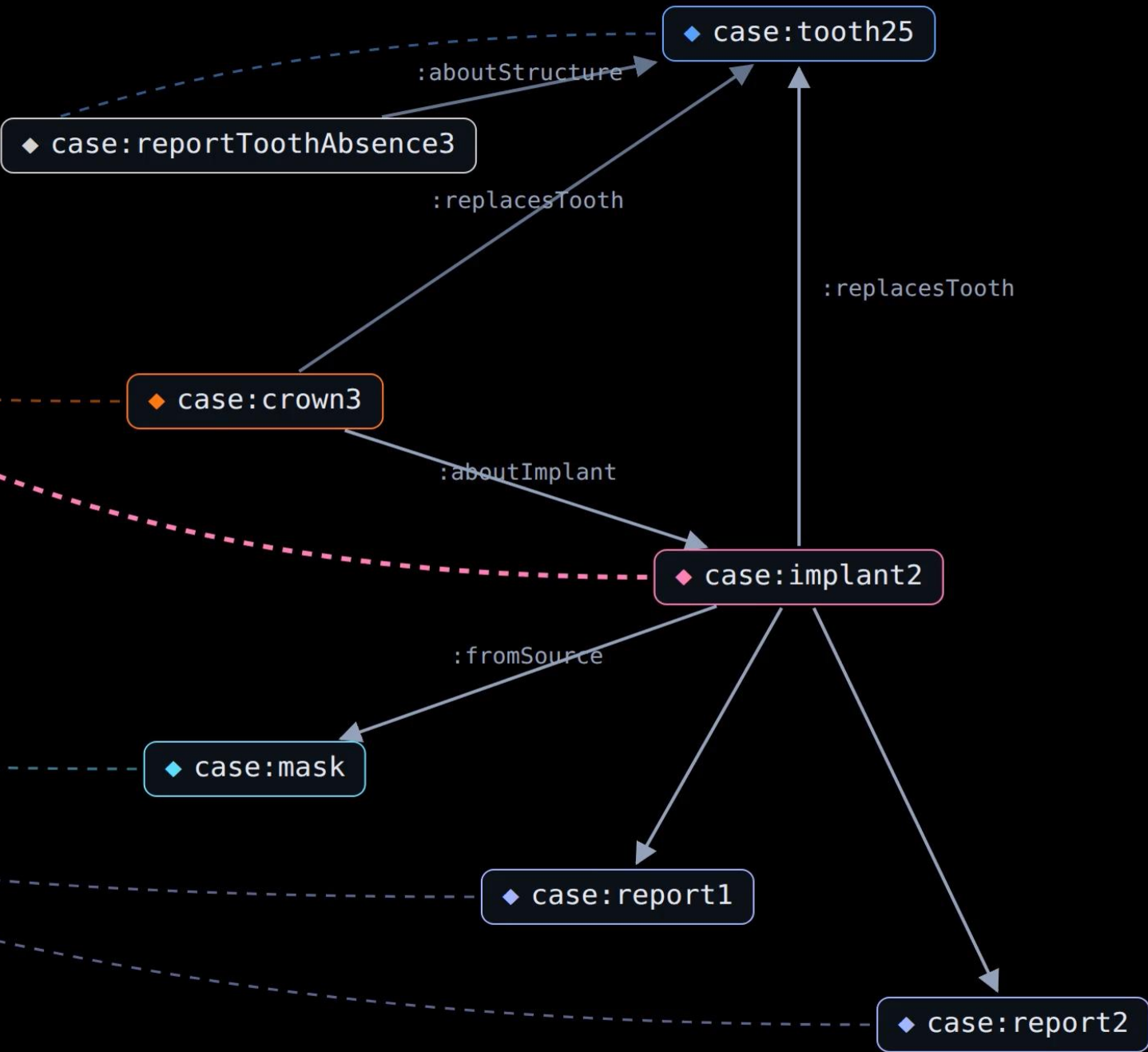
`:aboutImplant` `Crown` → `Implant`

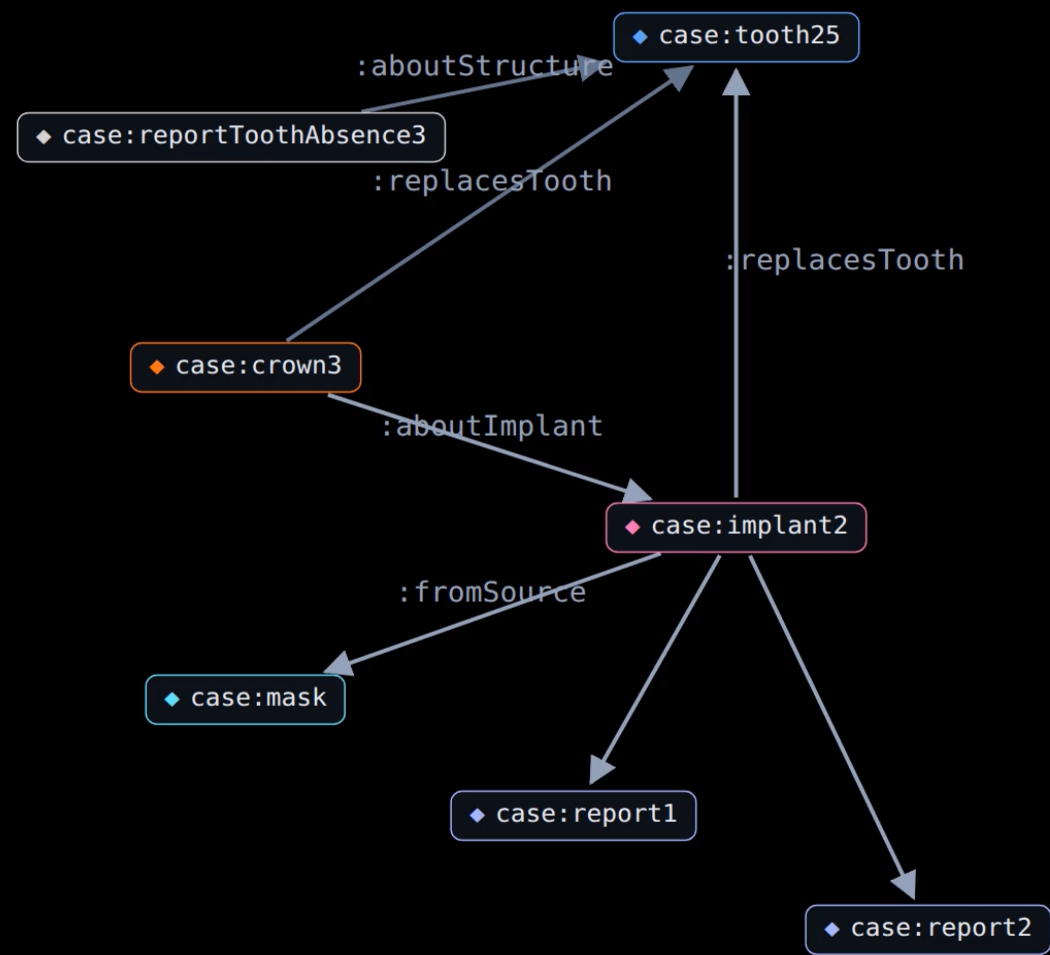
`:fromSource` `Finding` → `Source`

`:aboutStructure` `Finding` → `AnatomicalStructure`

PATIENT GRAPH `patient.ttl`

This patient's individuals and their links





References, not copies. The graph holds facts, their provenance and the names of the mask and report files. It does not contain the CBCT voxels or the mask geometry: a segment keeps only its bounding box, centroid and volume.

TURTLE data/ttl_report/patient.ttl (EXCERPT)

mask reports both merge

```
@prefix : <https://ditto.ing.unimore.it/toothfairy/ontology#> .
@prefix case: <https://ditto.ing.unimore.it/toothfairy/data/patient#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .

case:implant2 a :Implant ;
  rdfs:comment "Implant-prosthetic rehabilitation of teeth 16-25.",
    "Presence of endosseous implants in positions 16 and 25, on which prosthetic reconstruction has already
  been performed." ;
  :boundingBox "272 307 208 289 321 245" ;
  :centroid "281.1 314.4 226.4" ;
  :fromSource case:mask,
    case:report1,
    case:report2 ;
  :replacesTooth case:tooth25 ;
  :segmentationLabel 10 ;
  :volume 83.808 .

case:mask a :SegmentationMask ;
  :filename "patient/mask/mask.nii.gz" ;
  :ofModality case:cbct .
```

ToothFairy5: from each patient's graph, a dataset of **questions and answers**.

QUESTION ANSWERING

Like a standard chatbot (e.g., **ChatGPT** or **Gemini**): you ask in plain words, it answers. Here the AI also reads the patient's **3D data: CBCT and/or IOS**.

HOW WE BUILD THE DATASET TO TRAIN THE CHATBOT



We **walk each patient's graph**: every path becomes a question, and the graph already holds the answer.

EXAMPLE OF QUESTION/ANSWER OF THE DATASET

Is tooth 38 in contact with the inferior alveolar canal?

Yes: its roots touch the left canal.

Which teeth have a restoration?

16, 26 and 46.

Are there any implants?

Yes, one implant in position 36.



3D view Attenuated MIP Reset 3D Axial 3D

Transpose axes Level

Window Reset contrast LAS RAS

+ **CBCT Assistant** volume loaded

Visual question answering



Ask anything about this volume

Answers are grounded on the axial, coronal, sagittal and 3D views on the left.

Ask a question about this CBCT...



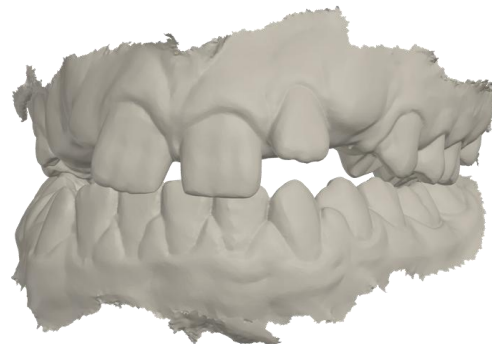
Scroll over a plane to step through slices · drag the 3D view to rotate

Four more building blocks toward a **fully automated orthodontic record**.

PHOTOS TO 3D SCAN



5 INTRAORAL PHOTOS



3D INTRAORAL SCAN

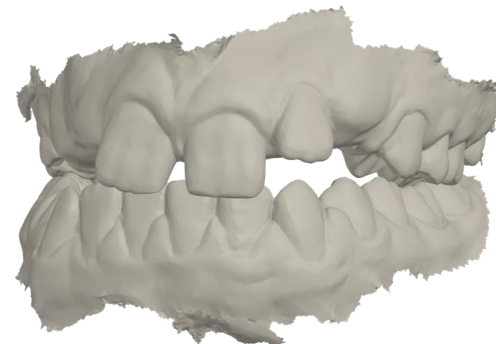
Reconstruct the patient's 3D intraoral scan directly from the five standard intraoral photos.

Four more building blocks toward a **fully automated orthodontic record**.

PHOTOS TO 3D SCAN



5 INTRAORAL PHOTOS



3D INTRAORAL SCAN

Reconstruct the patient's 3D intraoral scan directly from the five standard intraoral photos.

TOOTH SEGMENTATION



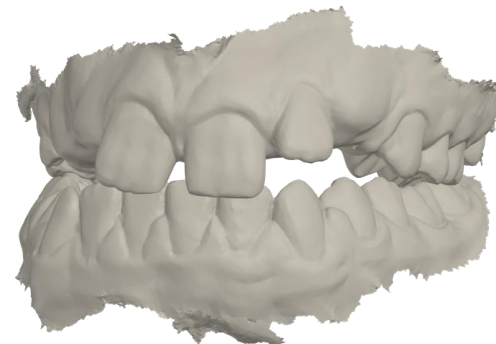
Segment every tooth and assign its FDI number in all the standard intraoral views.

Four more building blocks toward a **fully automated orthodontic record**.

PHOTOS TO 3D SCAN



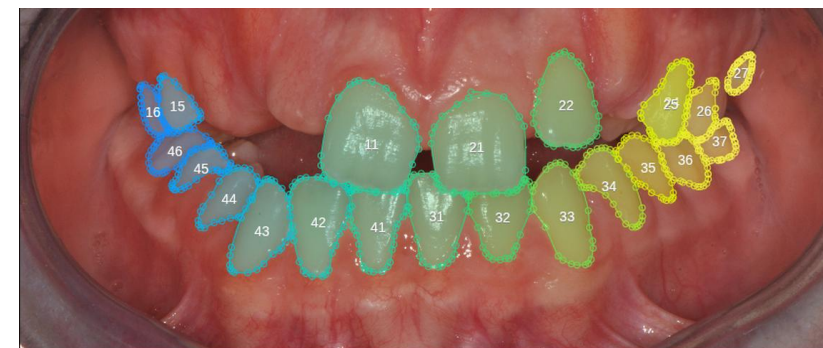
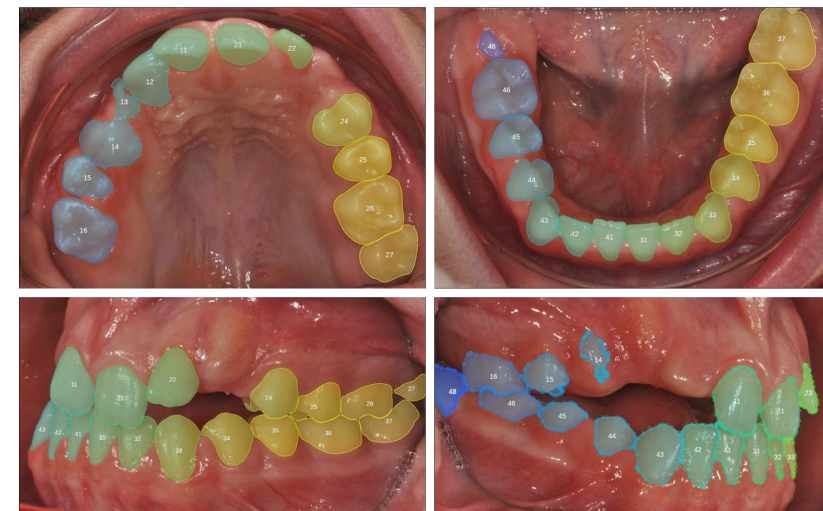
5 INTRAORAL PHOTOS



3D INTRAORAL SCAN

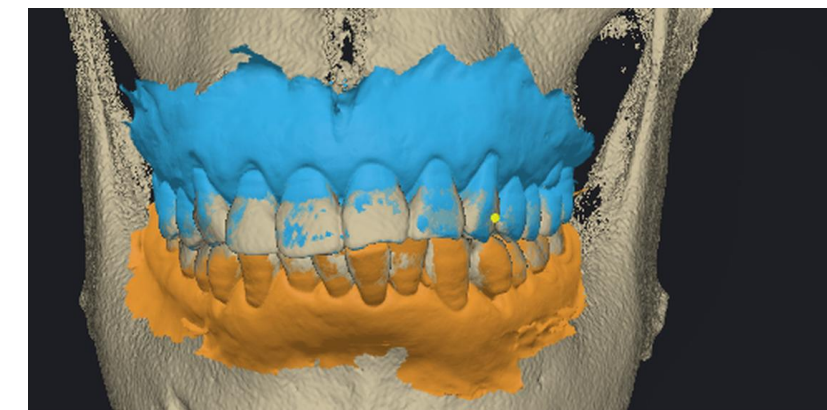
Reconstruct the patient's 3D intraoral scan directly from the five standard intraoral photos.

TOOTH SEGMENTATION

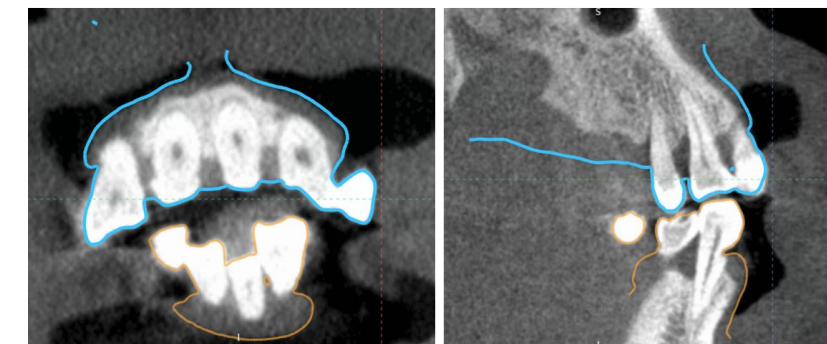


Segment every tooth and assign its FDI number in all the standard intraoral views.

IOS-CBCT REGISTRATION



IOS + CBCT (3D VIEW)



CORONAL

SAGITTAL

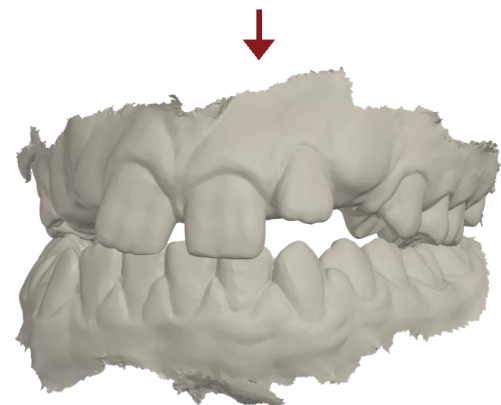
Register the intraoral scan on the CBCT, to retain benefits from both modalities.

Four more building blocks toward a fully automated orthodontic record.

PHOTOS TO 3D SCAN



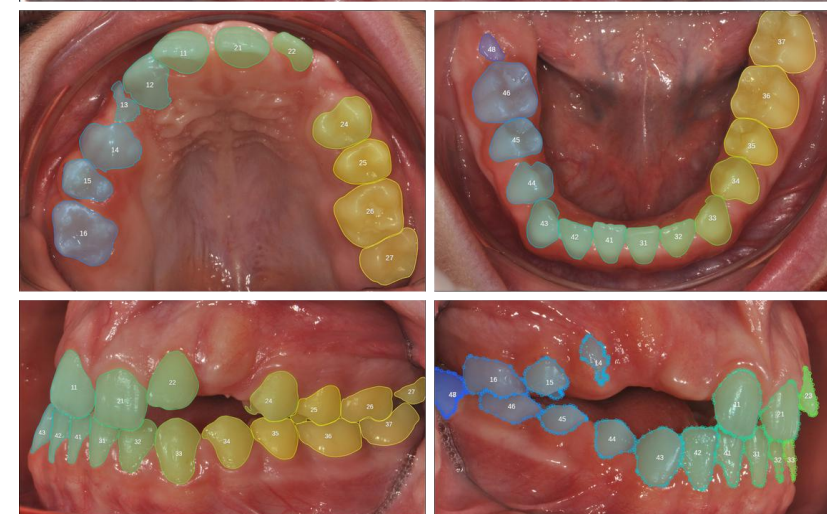
5 INTRAORAL PHOTOS



3D INTRAORAL SCAN

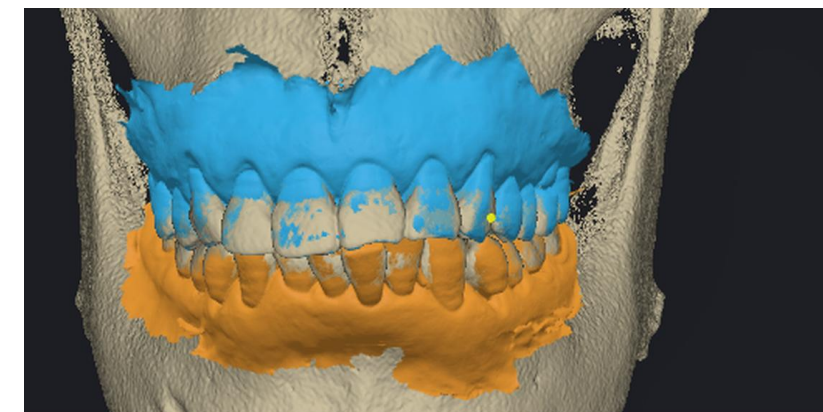
Reconstruct the patient's 3D intraoral scan directly from the five standard intraoral photos.

TOOTH SEGMENTATION

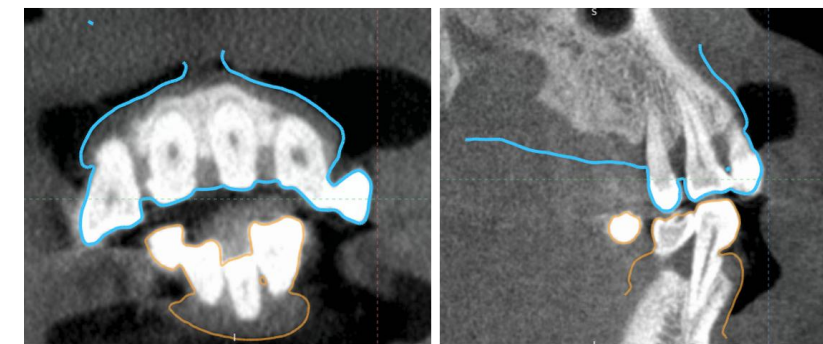


Segment every tooth and assign its FDI number in all the standard intraoral views.

IOS-CBCT REGISTRATION



IOS + CBCT (3D VIEW)



CORONAL

SAGITTAL

Register the intraoral scan
on the CBCT, to retain
benefits from both modalities.

VIEW CLASSIFICATION



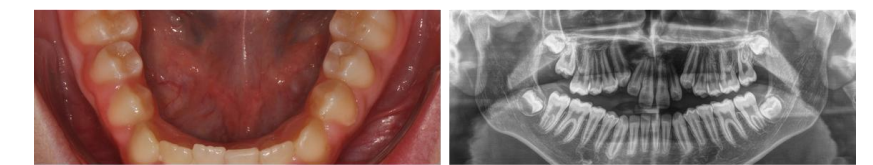
FRONTAL

UPPER OCCLUSAL



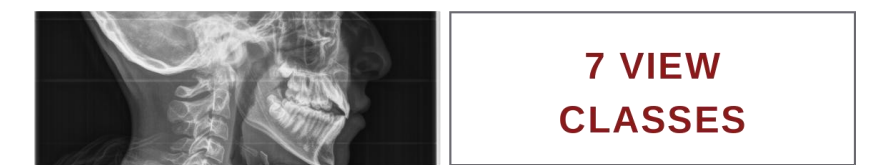
RIGHT LATERAL

LEFT LATERAL



LOWER OCCLUSAL

PANORAMIC



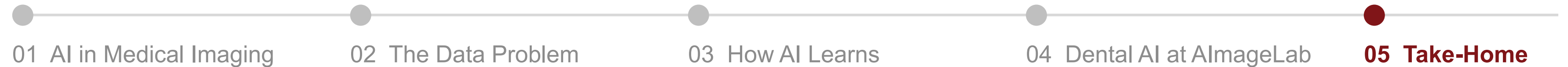
CEPHALOMETRIC

7 VIEW CLASSES

Automatically classify images:
five IOP views, panoramic and
cephalometric X-rays.

Take-Home

What a machine that learns from us asks of us, as clinicians.



“We can know **more** than we can tell.”

Michael Polanyi, *The Tacit Dimension*, 1966

01 YOU SEE IT

You recognize a good occlusion before you can explain why.

02 YOU LABEL IT

A landmark, a segmentation or a report makes that judgement explicit.

03 THE MACHINE LEARNS IT

The model learns only what your labels make explicit, nothing more.

AI in orthodontics will be as good as the data and the evaluation you help build.

01

AI learns from your data

Standardized acquisition (protocols, views, scanners) is the first step.

02

Your expertise is the scarce resource

Labels, reports and blind judgements: AI cannot exist without them.

03

Trust evidence, not demos

Ask: tested on which patients? On a public benchmark? Graded by whom?

04

AI is a second reader

It removes mechanical work. The clinical decision stays with you.

AIMAGELAB — UNIVERSITY OF MODENA AND REGGIO EMILIA

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G. Rosati



Y. Assefa



M. Lugli



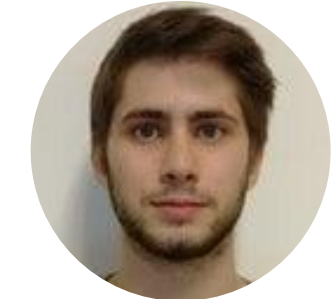
A. Veronese



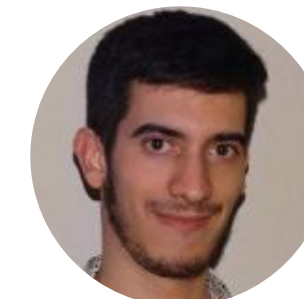
C. Grana



L. Lumetti



F. Pollastri



E. Vezzali

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COLLABORATIONS

Come Impara l'Intelligenza Artificiale

Dati, paradigmi di apprendimento e ricerca applicata all'imaging dentale

Thank You!

Federico Bolelli

AlmageLab — University of Modena and Reggio Emilia · federico.bolelli@unimore.it



UNIMORE
UNIVERSITÀ DEGLI STUDI DI
MODENA E REGGIO EMILIA



Papers, datasets, code