Standardized CT and dual-view X-ray workflow for AI-supported post-mortem broiler inspection

Feasibility study in a physical organ holder: data collection, processing, labels, and model evaluation

physical organ holder

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What this presentation will show

1 Problem

Why imaging support may help under high throughput inspection.

2 Feasibility step

Why we use a physical organ holder before harder carcass settings.

3 CT block

Can AI identify heart and liver in the CT volume?

4 X-ray block

Can paired AP + lateral X-rays classify health status?

5 What it means

Whether the results justify continuing and what must be tested next.

Main framing

Aim is to see whether continuing AI model building in this setup makes scientific sense.

Why poultry inspection needs support

Visual inspection remains valuable; the challenge is speed and internal findings.

WHY

High throughput

Many carcasses pass per minute, leaving only seconds for each bird.

Internal or subtle findings

Changes related to organ health, quality, welfare, or contamination may not be obvious from the outside.

Decision support

Findings still need to support decisions on fitness for human consumption and other inspection outcomes.

What imaging may add

An objective way to make internal anatomical and tissue patterns visible and support early inspection decisions.

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From previous CT evidence to today’s feasibility step

Experiments test whether it makes sense to continue model building in a more complex setup.

1 Previous isolated-organ CT work

CT scans could be used to diagnose individual isolated organs for health status (Libera et al.)2025.

2 New feasibility step

Place heart and liver in a physical organ holder that represents the carcass cavity but keeps experimental control.

3 Application-related question

After scanning, AI should first identify the organ region and then classify healthy versus diseased status.

Today’s presented results

CT feasibility result

Can the model identify heart and liver in the CT volume despite surrounding organs/tissues?

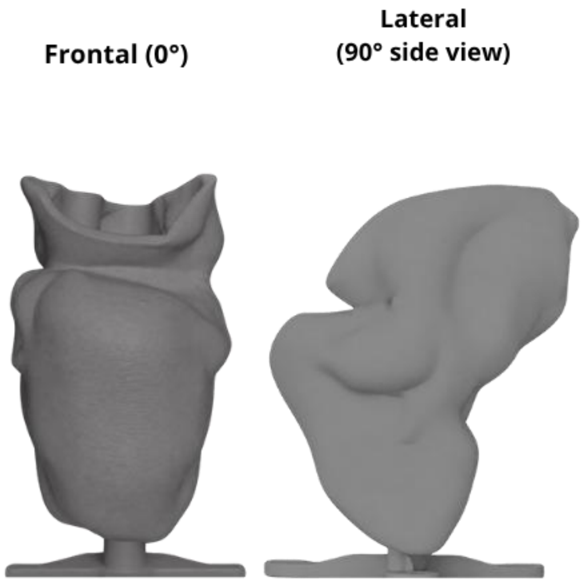
X-ray feasibility result

Can paired AP + lateral X-rays classify healthy versus diseased status from the same organ-holder setup?

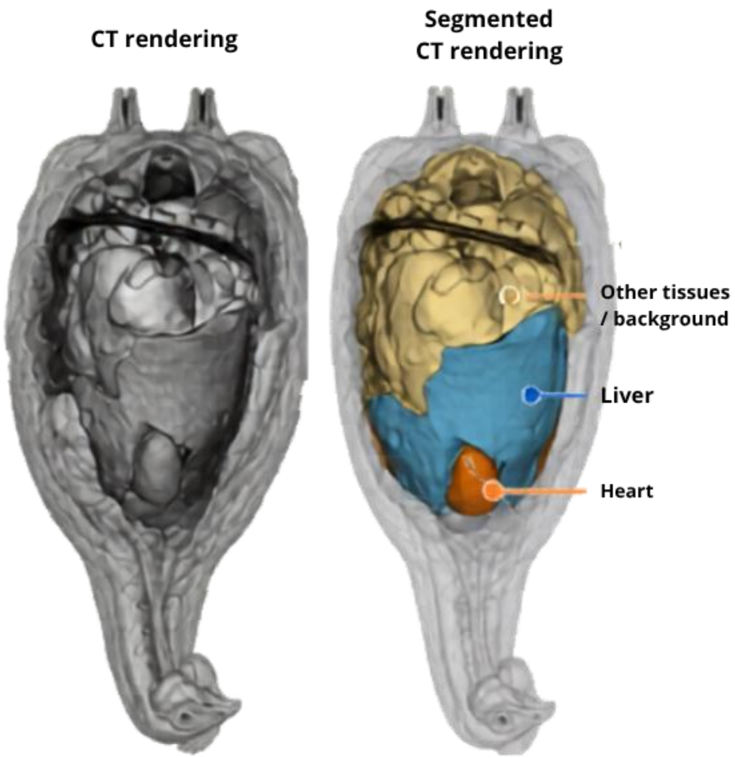
Why the physical organ holder, and why CT plus X-ray?

1) Reference anatomy: hanging chicken carcass

2) Physical organ holder

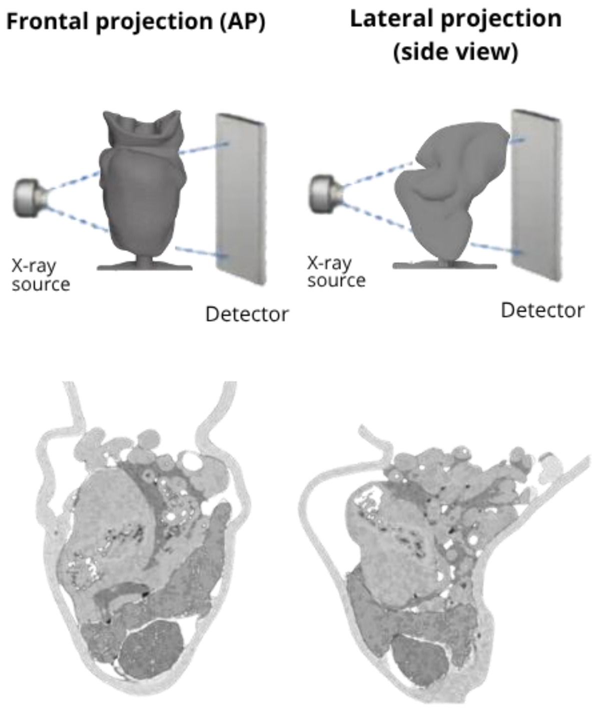


3) Inside the holder (CT)



Heart and liver can be visualized inside the holder.

4) Standardized dual-view X-ray input



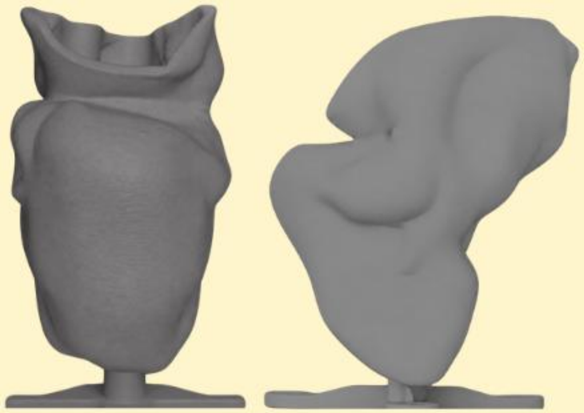
The organ holder is an experimental setup to continue AI model building with more control than whole carcasses.

Why the physical organ holder, and why CT plus X-ray?

1) Reference anatomy: hanging chicken carcass

2) Physical organ holder

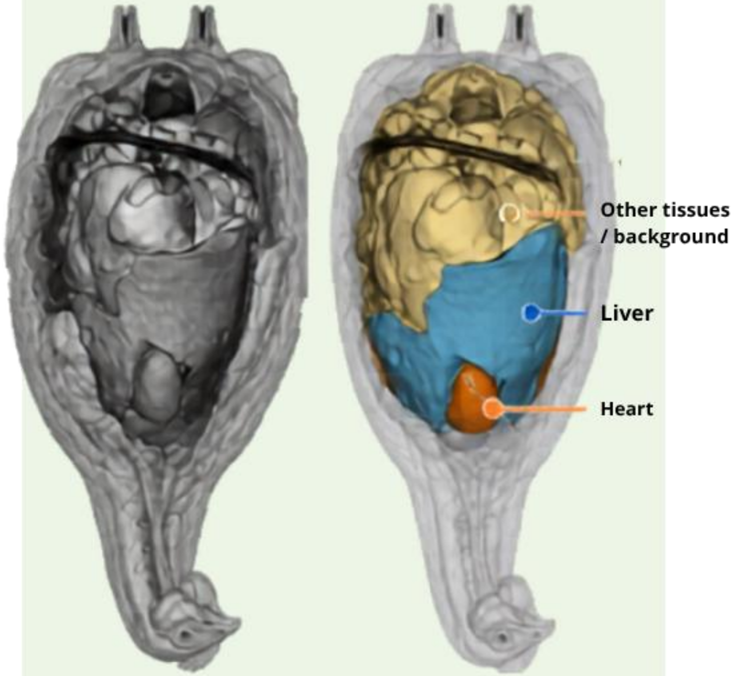
(0° front view) **(90° side view)**



Represents heart and liver in a carcass-like cavity while preserving experimental flexibility.

3) Inside the holder (CT)

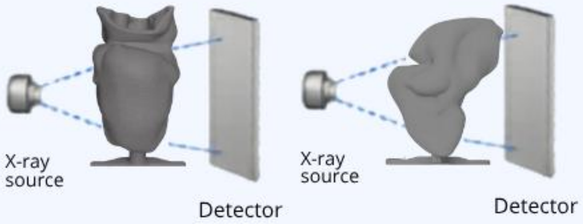
CT rendering **Segmented CT rendering**

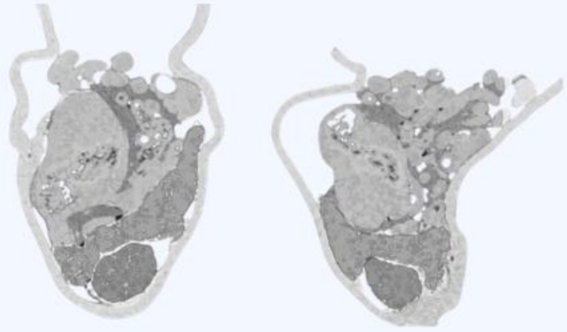


3D information. Better anatomical view. Useful for organ identification and reference development, but more equipment and time-intensive.

4) Standardized dual-view X-ray input

Frontal projection (AP) **Lateral projection (side view)**

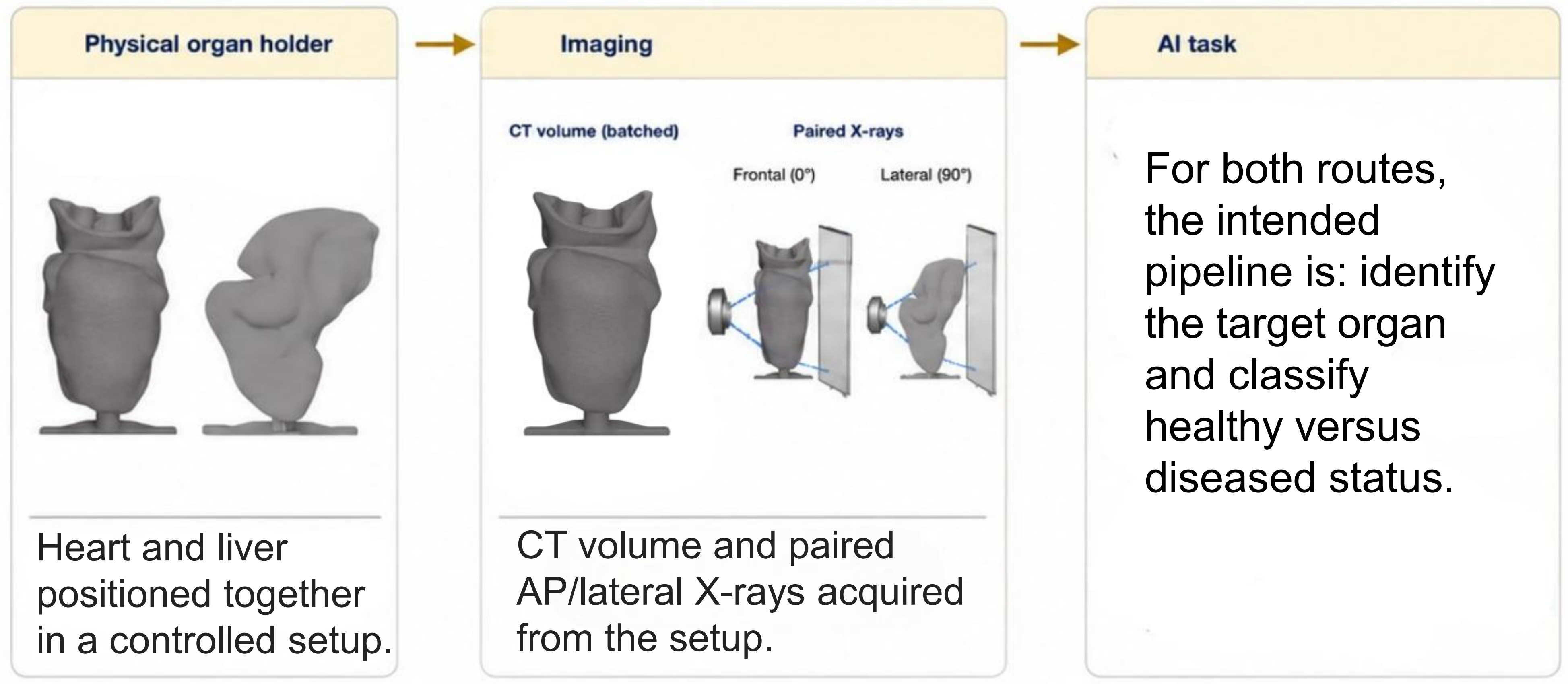




Limited 2D views, but faster and less space-consuming. Useful for testing a more practical screening route.

Where today's CT and X-ray results fit in the AI pipeline

Both imaging routes ultimately need organ identification and health-status classification.



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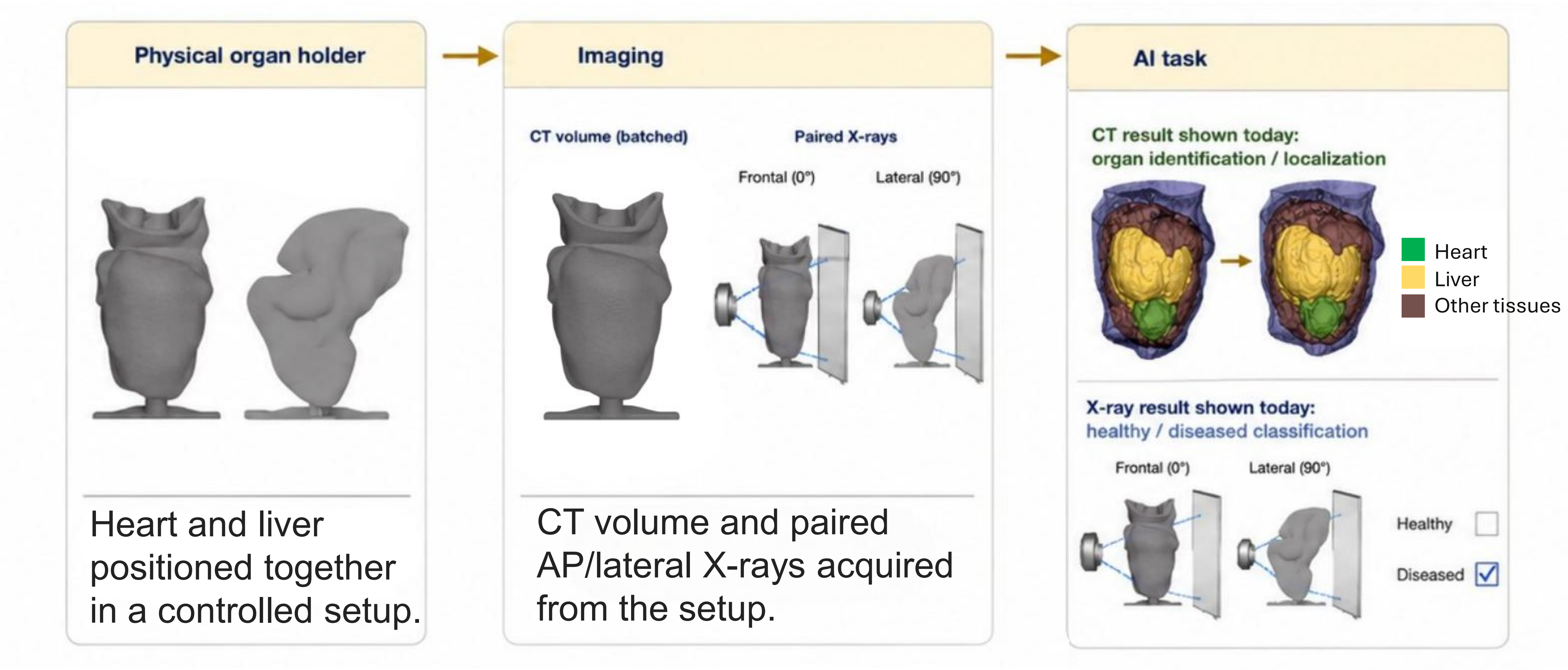

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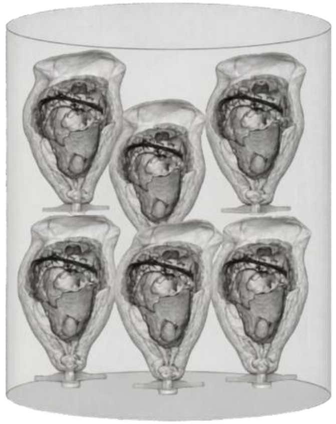
CT procedure: from batched scan to model prediction

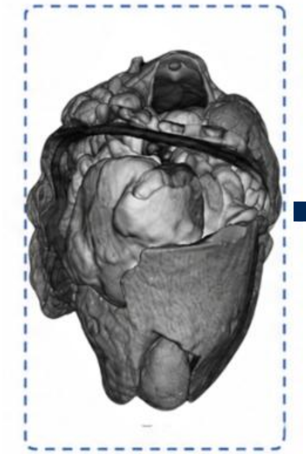
This process creates CT data that can be used for organ identification.

CT

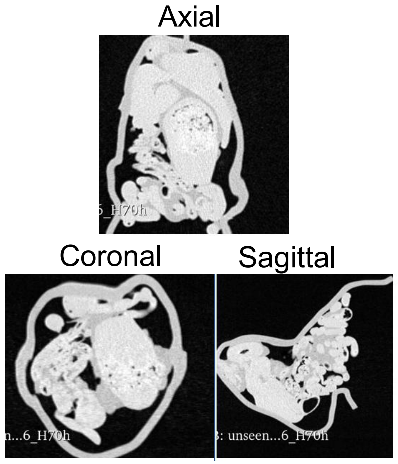
1 Batched CT acquisition



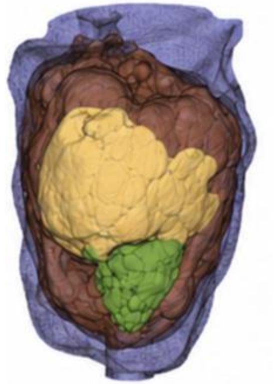
2 Manual extraction/ Cropping of one individual



3 Standardized refined crop around heart and liver

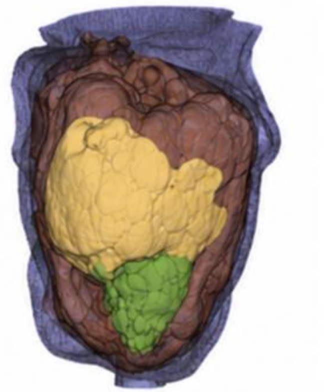


4 Manual reference segmentation in 3D Slicer



Heart
Liver
Other tissues /background

4 3D U-Net Prediction output



1. Batch scan

20 organ-holder cases are scanned together in one CT acquisition.

2. Individual extraction

One organ holder is manually extracted/cropped from the batch volume.

3. Refined crop

The heart–liver region is cropped in a consistent way to reduce irrelevant tissue.

4. Manual mask

Heart, liver, and other/background tissue are manually labelled in 3D Slicer.

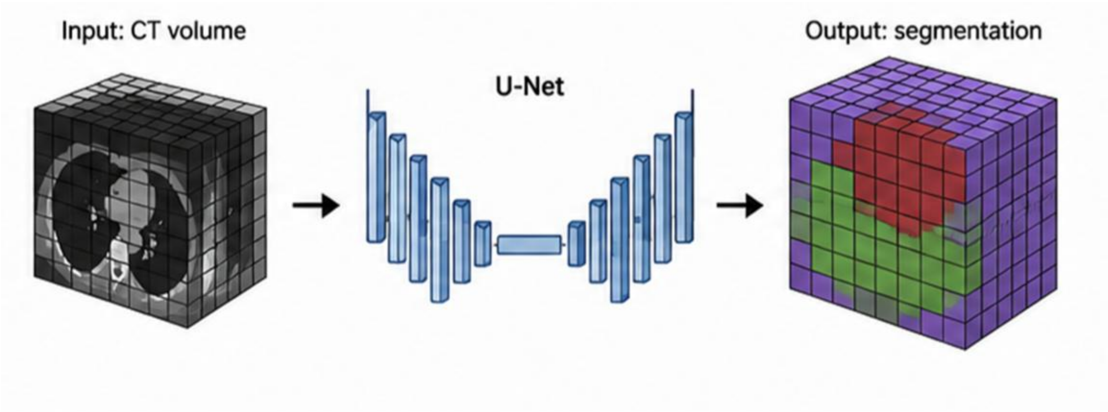
5. Prediction

A 3D U-Net predicts the same labels.

What the CT model is trained to do

The CT result is about voxel-wise organ identification, not disease classification.

CT



Voxel

A voxel is a tiny 3D pixel inside a CT volume. Each voxel can receive a tissue label.

AI modelling approach

A 3D U-Net is trained to predict the voxel label map from the CT crop.

Reference labels

Manual segmentation assigns each voxel to heart, liver, or background/other tissue.

Evaluation

Dice measures overlap between manual reference segmentation and model prediction.

Classes scored in this CT task

- 0 = background / other tissue
- 1 = heart
- 2 = liver

For every voxel, the model predicts which class it belongs to.

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3D U-Net CT segmentation: first result

Can the model identify heart and liver in the CT volume despite surrounding organs/tissues?

CT

[redacted]

Data

37 CT organ-holder cases
30 training / 7 validation

Best mean validation Dice

[redacted]

Interpretation

The model learned organ-localization signal, but this is not yet robust enough for application.

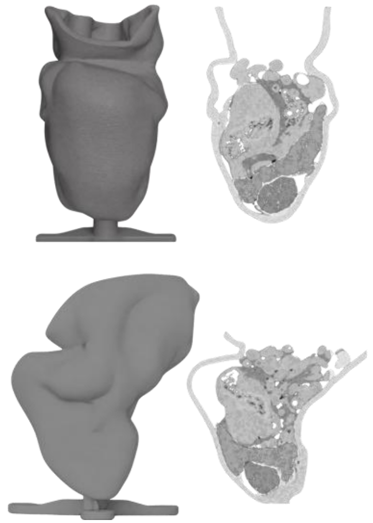
How to read this

The Dice score summarizes spatial overlap between the manual organ masks and the U-Net prediction. A value around [redacted] supports feasibility but also shows that refinement and more data are needed.

X-ray procedure: same case, two standardized projections

The X-ray route tests a faster, less equipment-intensive screening direction.

X-RAY



AP/frontal projection

One standardized 2D view from the organ-holder setup.

Lateral projection

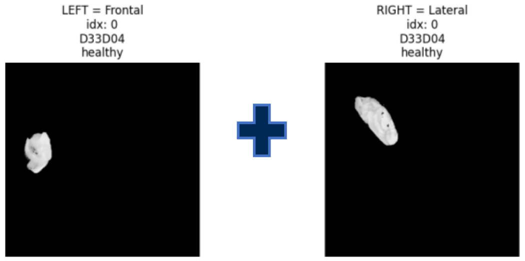
Second standardized 2D view from the same biological case.

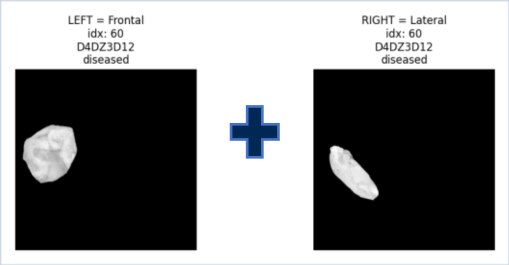
Paired input

AP/frontal + lateral images are kept linked to one case and one health label.

Classifier output

Healthy or diseased status for the organ/case.





Example masked paired X-rays: heart and liver

The hypothesis that one projection might be sufficient remains open; today's result uses paired AP + lateral views.

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X-ray classification: labels, input, and evaluation

Here the scored label is healthy/diseased status, not voxel localization.

X-RAY

Heart dataset

94 complete paired heart cases
49 healthy / 45 diseased

Liver dataset

97 complete paired liver cases
52 healthy / 45 diseased

Model input

Masked AP/frontal image + masked lateral image from the same case.

Evaluation

5-fold stratified cross-validation; predictions from the test folds are summed.

What is scored?

The model predicts healthy or diseased status. Performance is summarized with ROC-AUC, accuracy, sensitivity, specificity, and the summed cross-validation confusion matrix (predictions from all five test folds combined).

Heart paired X-ray classification result

can paired 2D views contain enough signal to classify health status?

X-RAY

Heart: updated aggregate five-fold result

94 paired cases | 49 healthy / 45 diseased

How to read the matrix

Rows are the true health status. Columns are the predicted status. The matrix combines predictions from all five cross-validation test folds.

Interpretation

In the controlled organ-holder setting, paired heart X-rays contain health-status signal. False positives and false negatives remain important.

Liver paired X-ray classification result

can paired 2D views contain enough signal to classify health status?

X-RAY

Liver: updated aggregate five-fold result

97 paired cases | 52 healthy / 45 diseased

[redacted]

Reporting note

These values come from the updated summed five-fold matrix. AUC can be added if calculated for the final liver run.

Interpretation

In the controlled organ-holder setting, paired liver X-rays also contain health-status signal. The result supports continuing with more data and more robust validation.

Next experiments before stronger application claims

The next work should strengthen the evidence inside the organ-holder workflow first.

NEXT

1 More data

Increase the number of organ-holder cases and scanning variation.

2 Robust models

Assess whether larger datasets improve accuracy and stability.

3 Sensitivity / specificity targets

Relate performance to what would be needed for inspection support.

4 Compare routes

Test how far X-ray can approximate CT-based information for the relevant tasks.

5 Complete task pairing

Continue CT classification and X-ray localization/segmentation experiments.

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Thank you — questions and discussion

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