PumonAI: Multi Institutional Collaboration via Federated Learning for Pneumonia Screening in Indonesia

Toward a Responsible AI

A Project supported by APNIC Foundation

Summary

01 Background and motivation

Pulmonary diseases, medical imaging, and responsible AI.

02 Architecture and training

Local data management, DenseNet-121, and deployment.

03 Communication and robustness

SVD compression and out-of-distribution detection.

04 Results and future directions

Computation time, performance, explainability, and future work.

AI in medical imaging

Artificial intelligence plays an increasing role in medical image analysis.

Abnormality detection

Identify abnormalities in medical images.

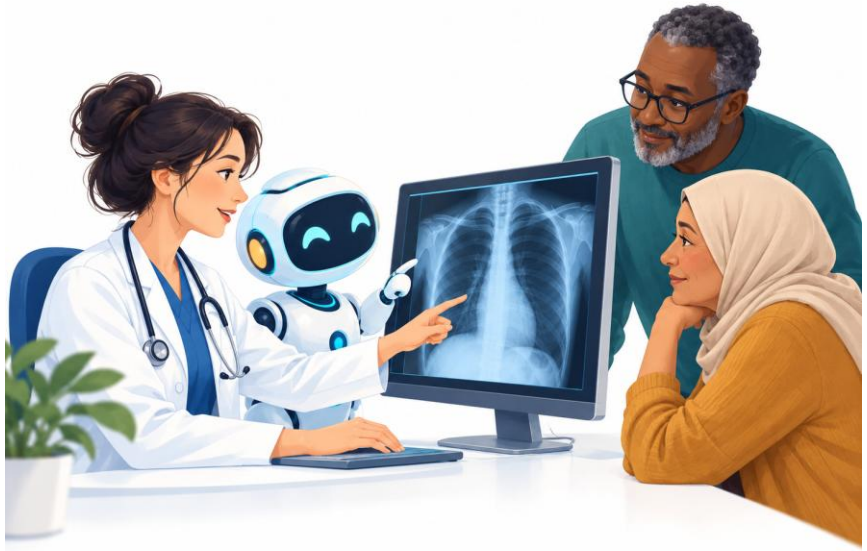
Diagnostic support

Improve diagnostic consistency and reduce analysis time.

Chest radiography

A widely used modality suitable for AI-assisted diagnostic tools.

Responsible AI



AI designed and used to benefit people, manage harm and uphold human rights and accountability.

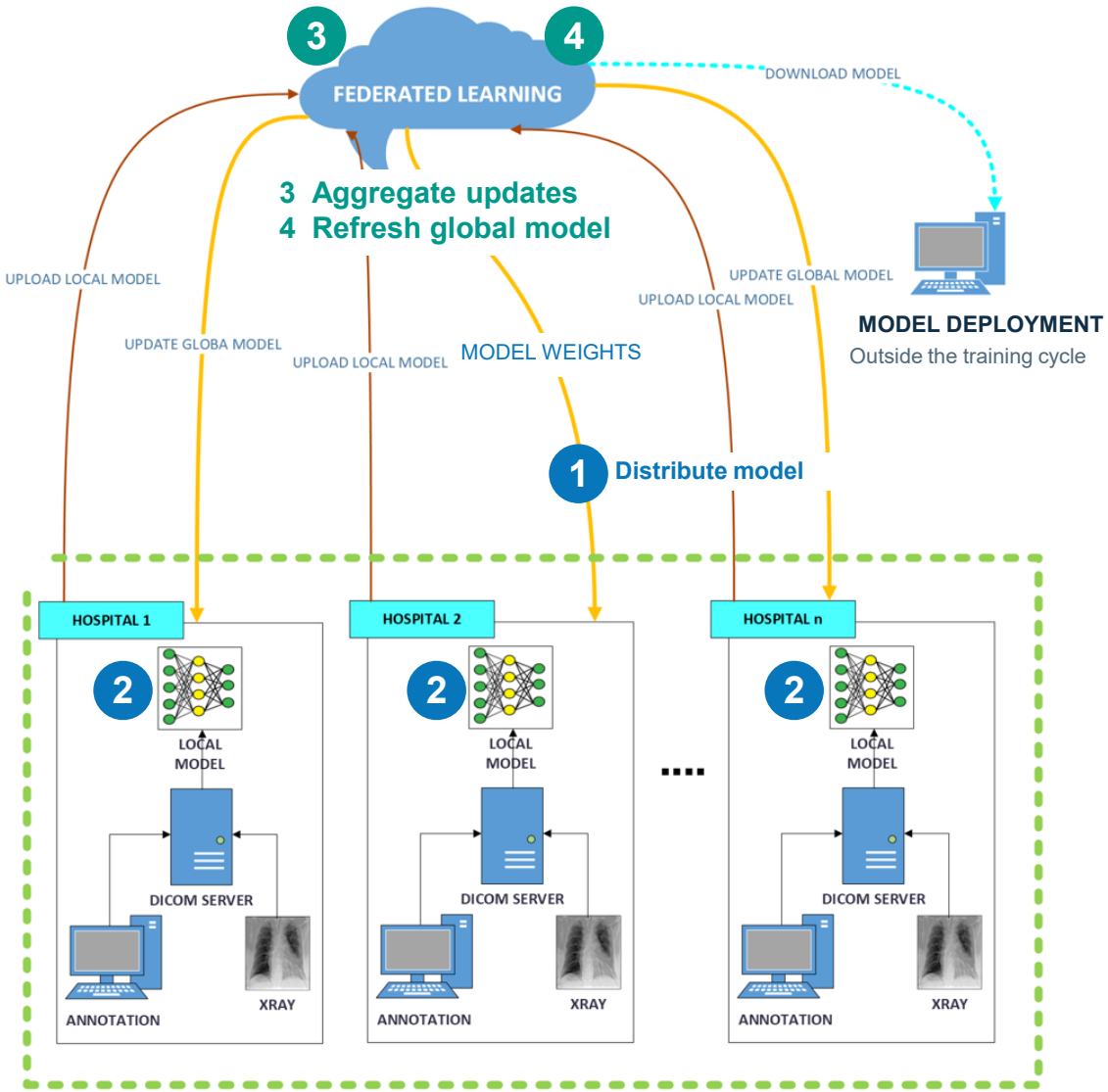
Trustworthiness AI deserves reliance through demonstrated reliability, safety, data protection and accountable human oversight.

Explainability AI provides understandable, faithful reasons for its outputs, so decisions can be inspected, questioned and audited.

Fairness AI avoids unjust disadvantage to particular communities, including harmful bias from imbalanced or unrepresentative data.

The federated learning training cycle

Model parameters move between sites. Patient data remain local.



1 Select and distribute

Select participating hospitals. Send model weights and training instructions.

2 Train locally

Each selected participant learns from its own data.

3 Combine and aggregate

Collect and combine model updates at the server. Apply timeout policies.

4 Synchronise

Apply the aggregate and refresh the shared global model.

Repeat steps 1–4 until the stopping criterion is met.

Only model parameters or updates leave each hospital; patient data stay local.

Local data management architecture

Local storage

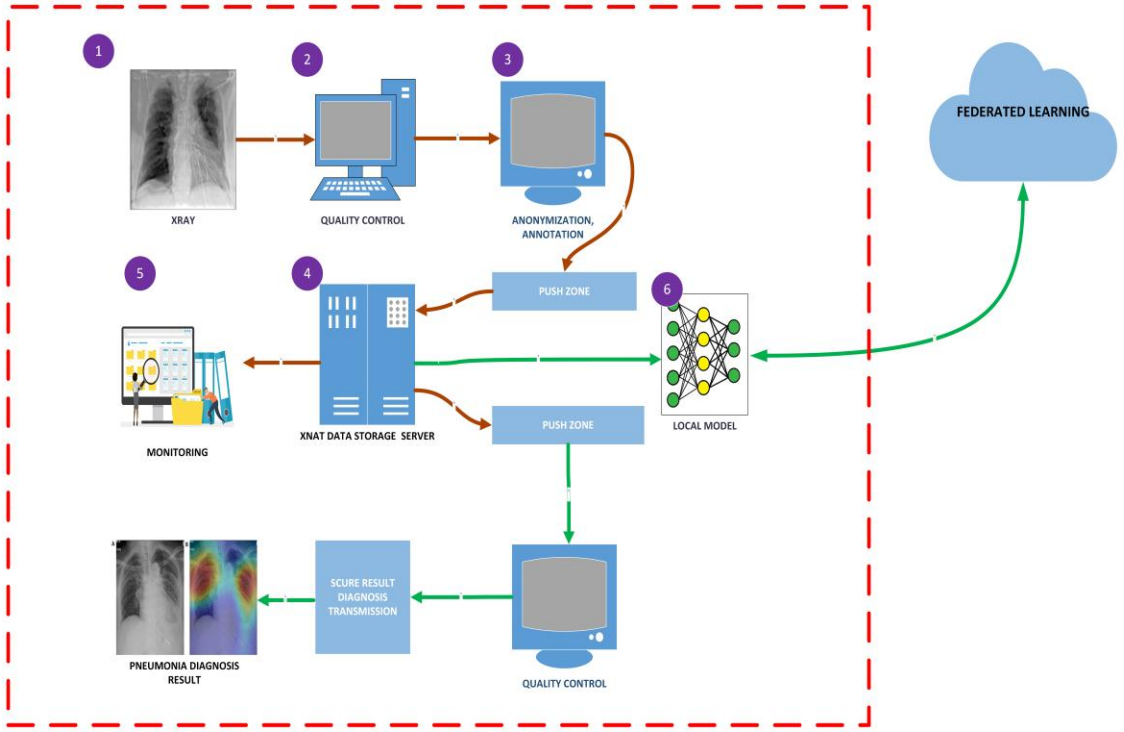
X-ray images remain on the hospital's XNAT server.

Data preparation

Review, anonymization and annotation take place locally.

Collaborative learning

Hospitals train local AI models and share updates for aggregation.



Dataset

NIH ChestX-ray14

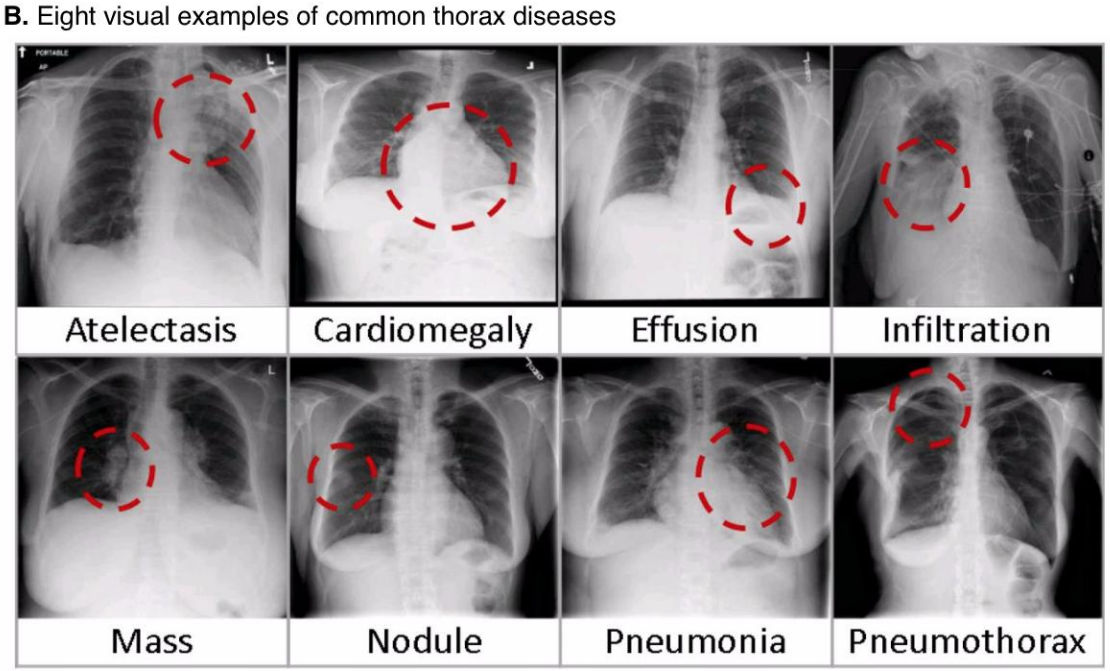
Approximately 100,000 chest radiographs.

Population

Approximately 30,000 patients.

Annotations

14 pulmonary conditions.



This dataset is widely used in medical imaging research.

Deep learning model

DenseNet-121

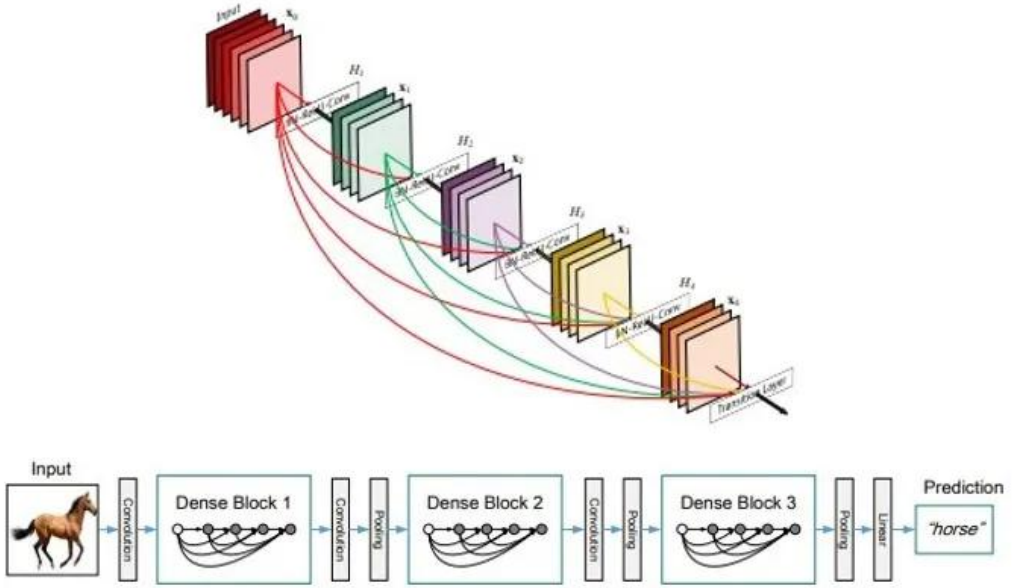
Efficient reuse of previously learned features.

Training benefits

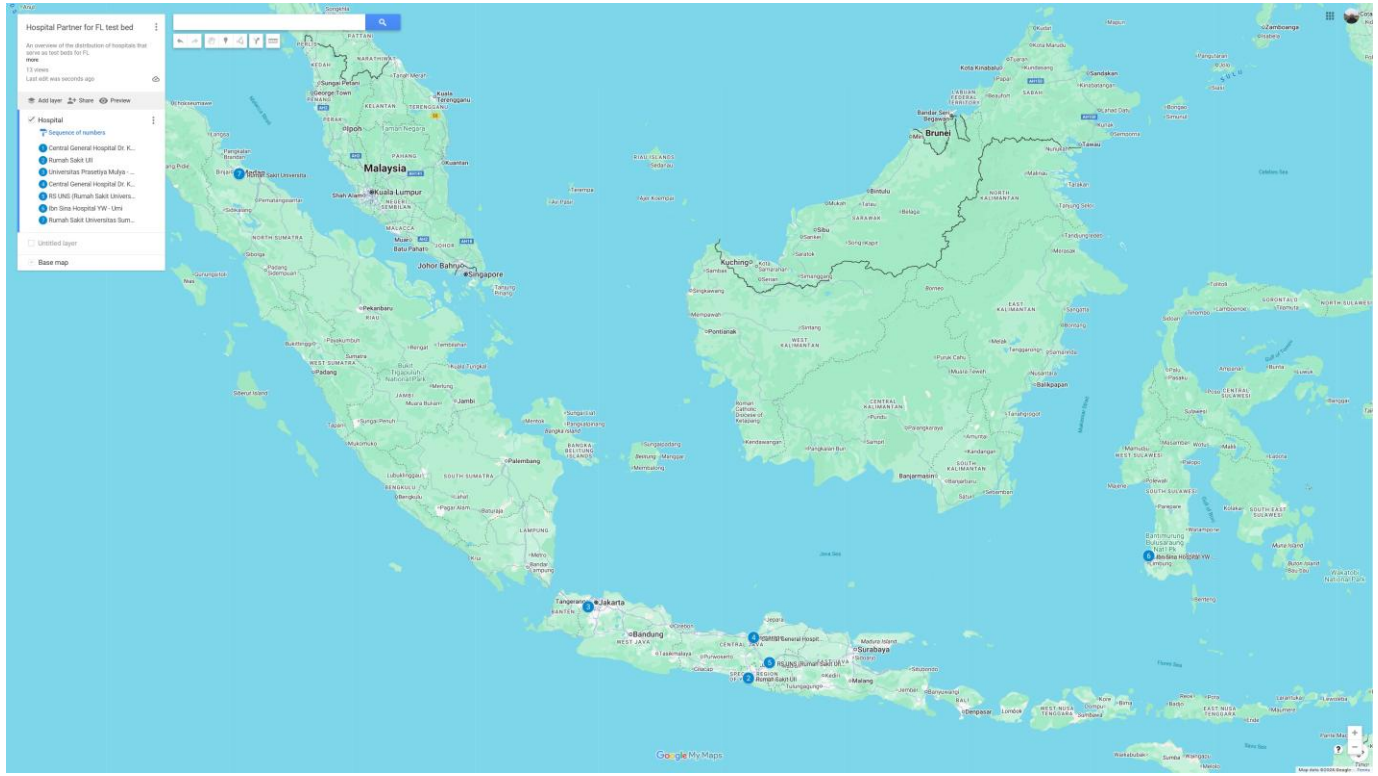
Improved gradient propagation and strong image classification performance.

Input images

Images are resized to 224 × 224 pixels before training.



Deployment infrastructure



7 hospitals

5 Located on the island of Java and
2 located at outside java

Central coordinating server

A dedicated server aggregates the models is in our university

Network latency largerly affect communication between participating hospitals.

Communication challenges

Federated learning requires frequent exchanges of large model parameters, usually deep learning model is huge.

Transmission volume

Each exchange can involve a substantial data payload.

Communication time

Model transfers increase the duration of training rounds.

Network load

Repeated exchanges place demands on connections between participants.

Communication becomes a limiting factor.

Model compression

Model compression reduces the cost of exchanging model parameters.

Reduce model size

Send fewer parameters or a compact representation.

Accelerate transmission

Reduce the volume transferred over the internet.

Preserve performance

Balance compression against model quality.

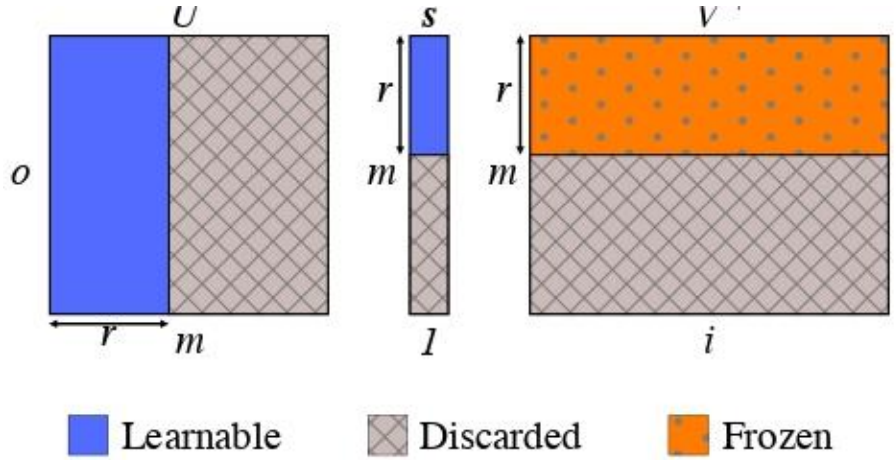
A useful approach for distributed learning.

Singular value decomposition (SVD)

SVD approximates a large matrix with fewer principal components.

$$A \approx U_r \Sigma_r V_r^T$$

Smaller model size
Faster transmission
Reduced network overhead



A: original matrix
U: left singular vectors
Σ: singular values
V^T: transposed right singular vectors

Out-of-distribution detection

Unexpected inputs

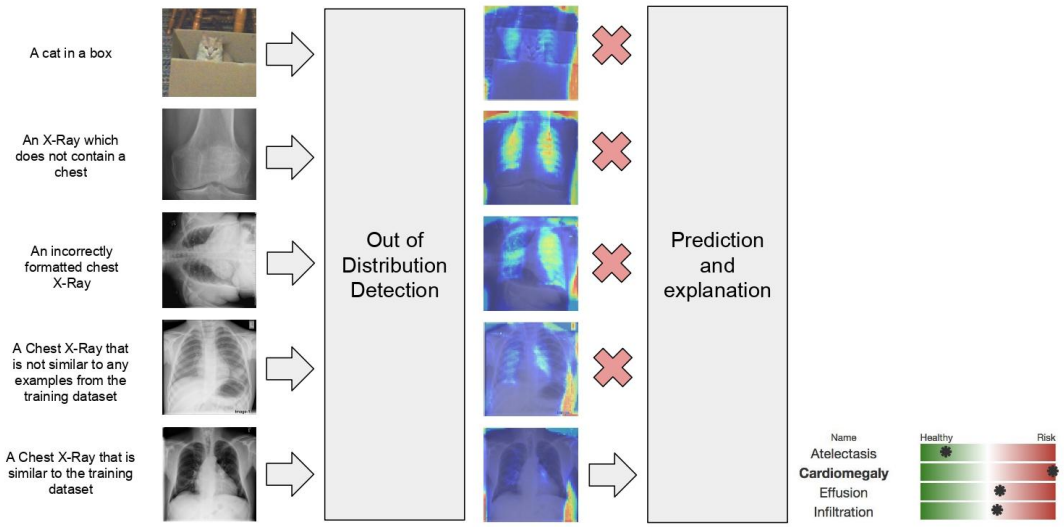
Images from another imaging modality.

Quality problems

Corrupted images.

Unrelated content

Non-medical images.



Unexpected inputs can lead to incorrect predictions, motivating OOD detection.

Autoencoder for anomaly detection

Learn reconstruction

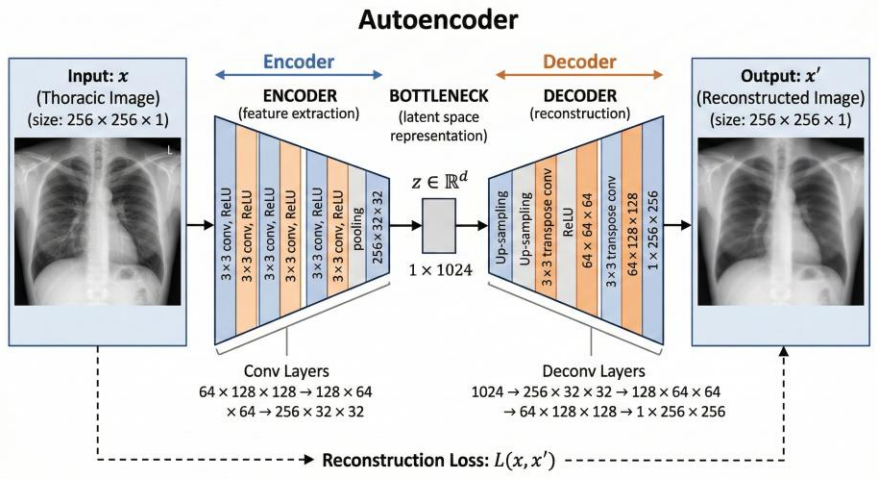
Train an autoencoder on normal chest X-rays.

Measure the mismatch

An unusual input can produce a larger reconstruction error.

Identify anomalies

Use reconstruction quality to flag anomalous inputs.

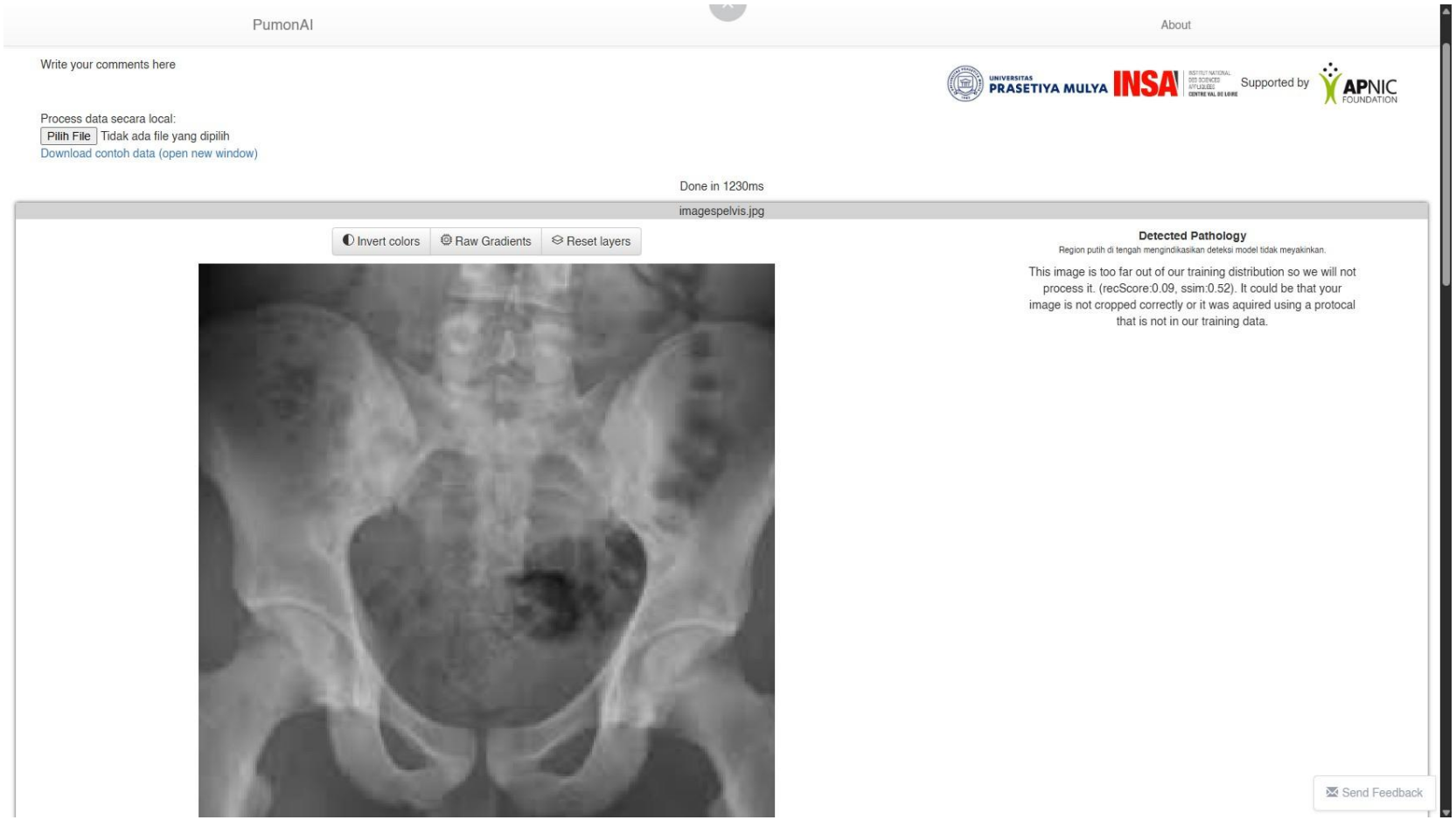


SSIM (Structural Similarity Index)

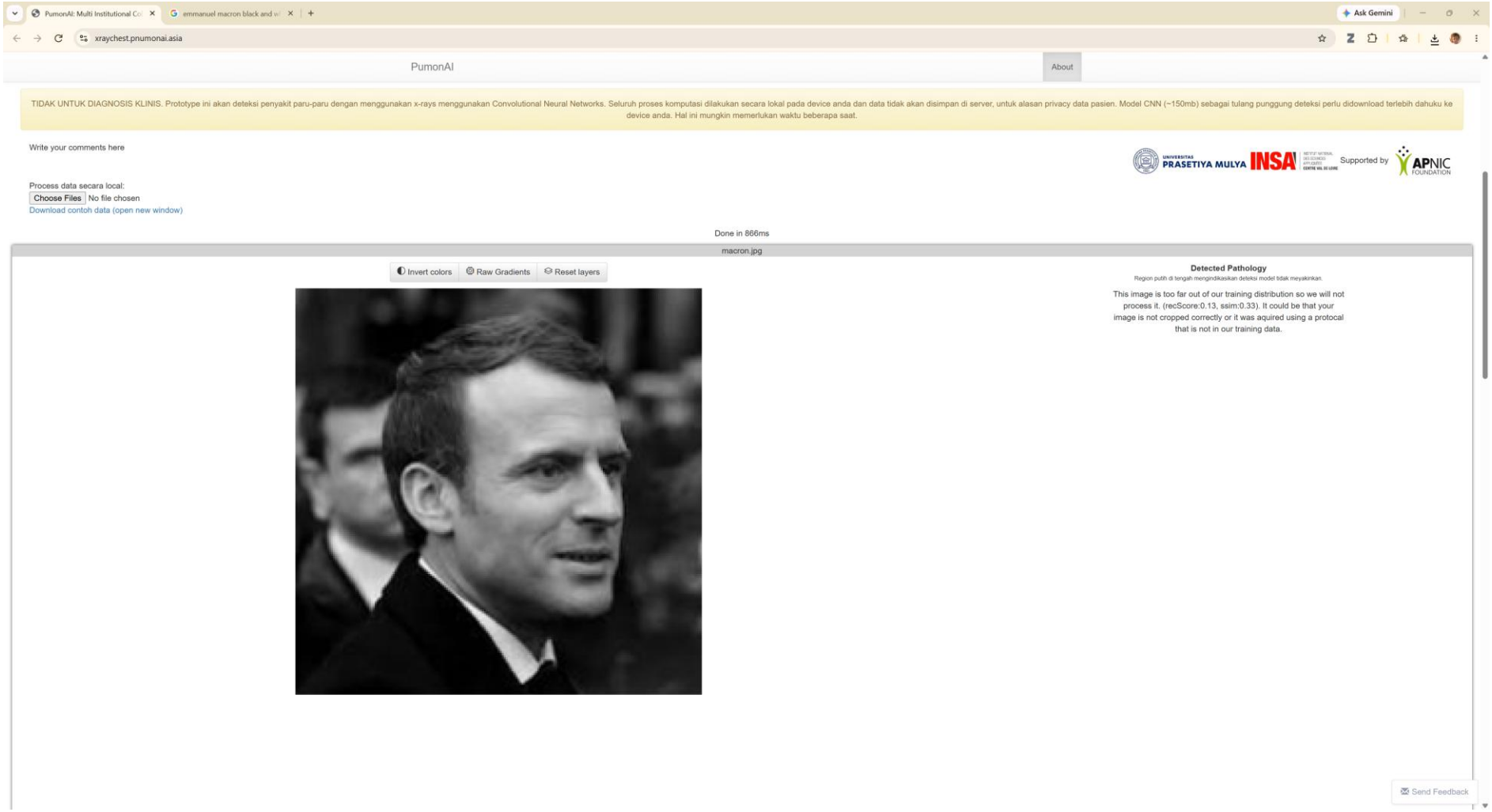
$$\mathrm{SSIM}(x,\hat{x}) = \frac{(2\mu_x\mu_{\hat{x}}+C_1)(2\sigma_{x\hat{x}}+C_2)}{(\mu_x^2+\mu_{\hat{x}}^2+C_1)(\sigma_x^2+\sigma_{\hat{x}}^2+C_2)}$$

Compares luminance (mean), contrast (variance), and structure (covariance).

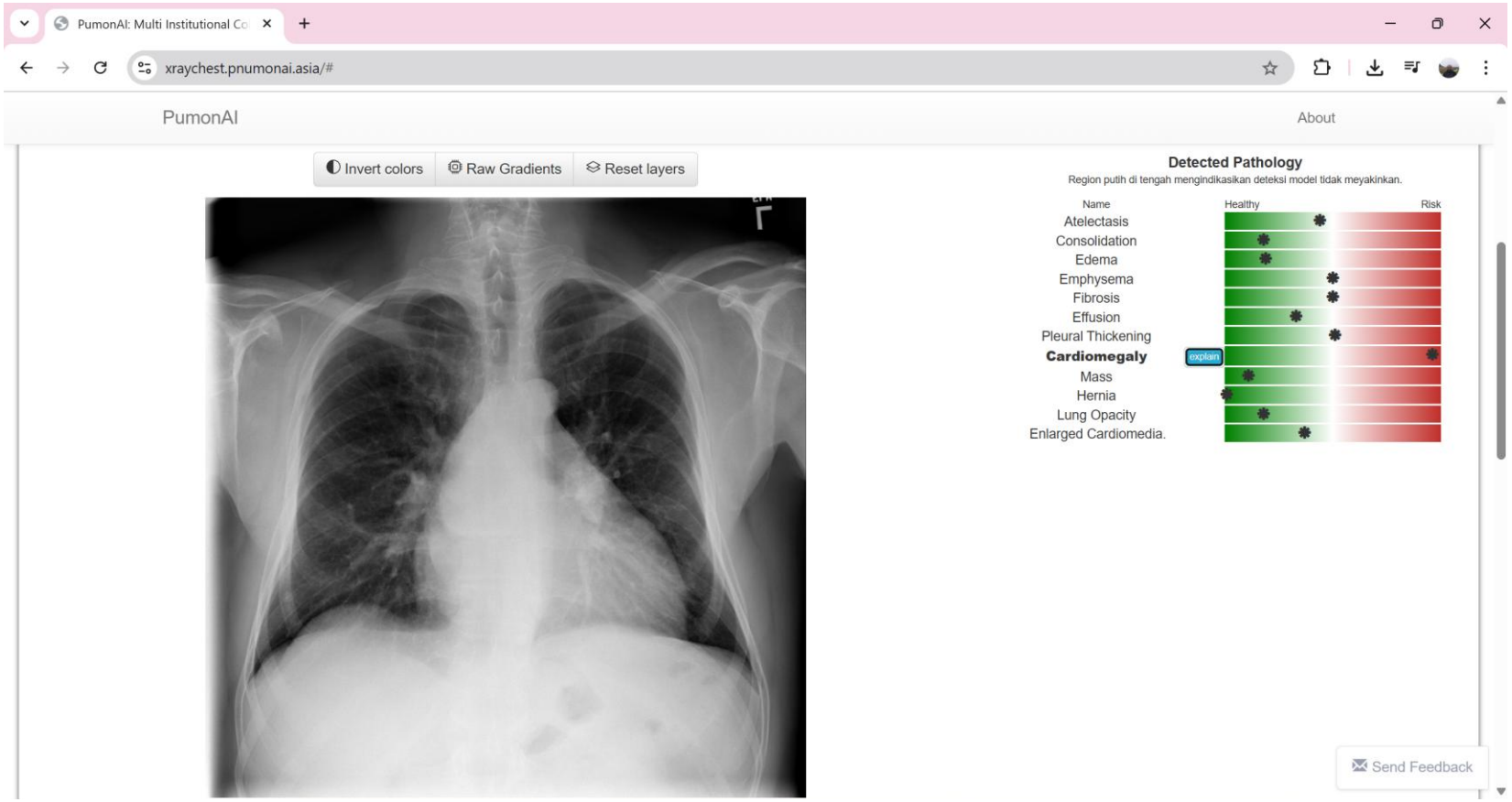
OOD detection



OOD detection



Privacy-preserving detection



Demonstration

https://xraychest.pnumonai.asia/

Benefits of the approach

Patients

Improved protection of personal data.

Hospitals

Collaboration without sharing raw data.

Researchers

Training on more diverse data, with the potential to reduce bias.

Conclusion

Federated learning

Enable collaboration while retaining data within hospitals.

Model compression

Reduce communication costs.

Robustness and explainability

Detect unusual inputs and interpret model predictions.

Privacy-preserving AI for distributed healthcare systems.

Future directions

Network expansion

Include more hospitals and collaborations across Southeast Asia.

Clinical integration

Integrate these tools into clinical workflows.

Bias

Investigate differences across populations and participating institutions.

Other sensitive domains

Explore applications in banking, finance, and government services.

Thank you

Questions and discussion