Transforming Thermal Images into Energy Savings using AI-Based Integrity Assessment of Insulated Piping Systems

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Importance of insulated pipeline

- Reduce heat loss during transport (lowering energy consumption and operational costs)
- Maintain optimal fluid temperature
- Prevent burns and injuries by high-temperature surfaces
- Extend equipment lifespan (minimizing thermal stress)

What happens when insulation breaks down ?

- **Energy Loss**
  damaged insulation layer, fallen-off insulation layer.
- **Pipe Leakage**
  due to the corrosion.
- **Product Quality Degradation**

HOW TO PREVENT?

Effective inspection and maintenance are essential to ensure the safe operation of the pipeline.

Assessment challenges: current limitations

On-site inspection

- **Visual Inspection**
  identify risk location by
  partially or entirely insulation removal
- **Ultrasonic Wave Testing**
  to evaluate the safety level of pipeline

Limitations

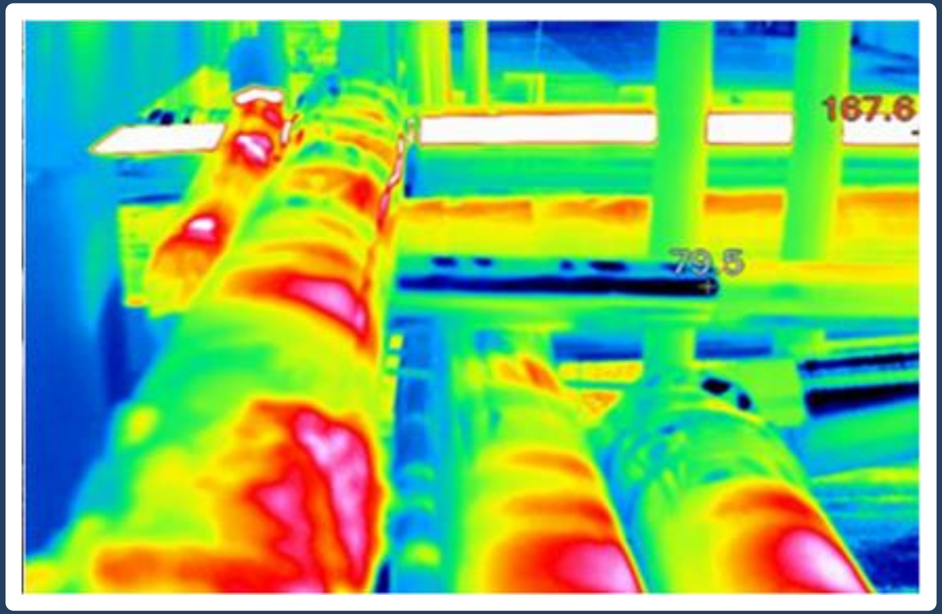
- Laber Intensive & Time-consuming
- Spot-Check Inspection
  (for partially remove the insulation)
- Depend on Inspector’s Experience

HOW TO INSPECT **WITHOUT**

REMOVING THE CLADDING and **INSPECTOR’S EXPERIENCE**

NON-Destructive Testing (NDT)

Artificial Intelligence (AI)

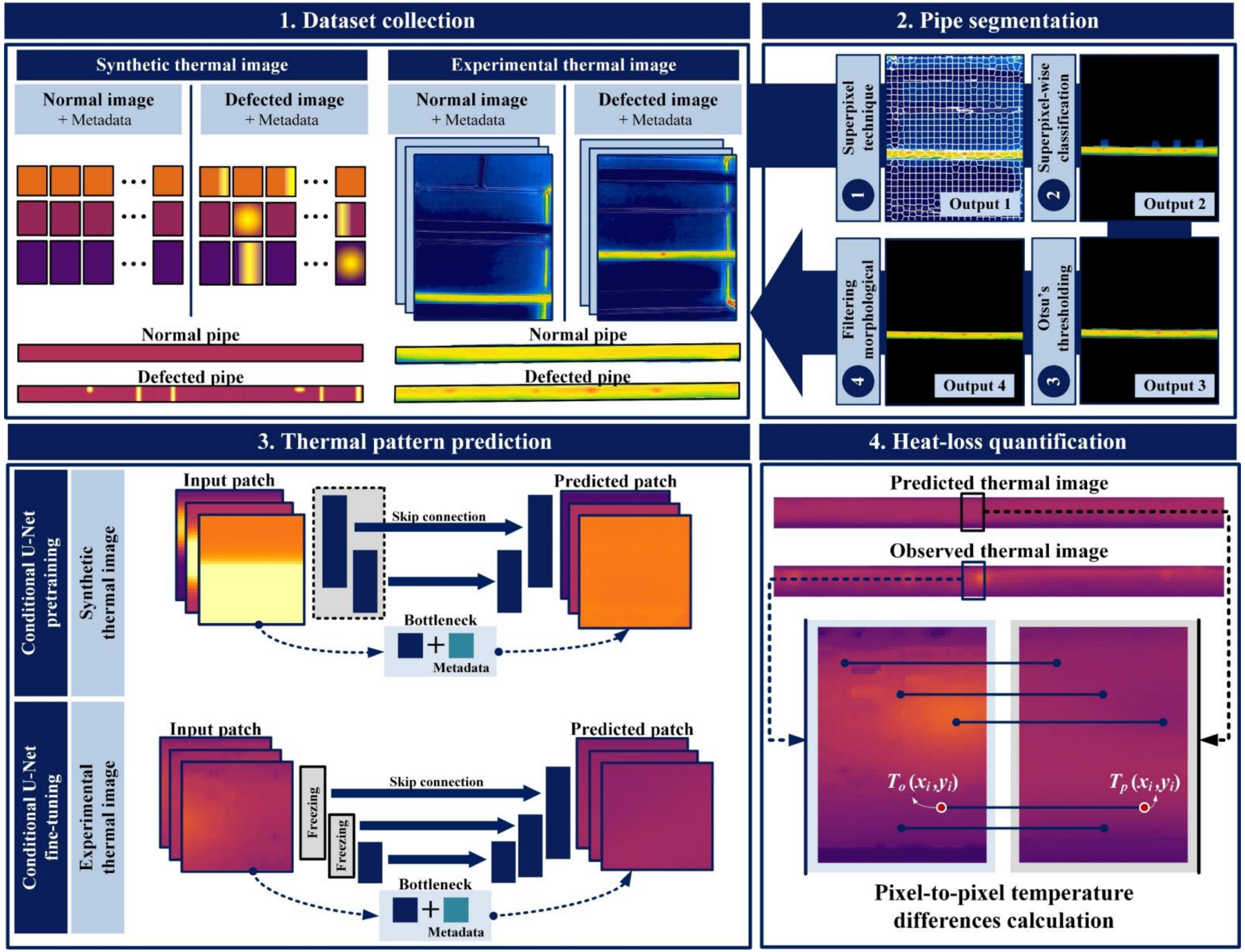


Infrared Thermography (IRT)

AI-based Algorithms

Solution: Combining NDT + AI

Proposed Framework: AI-Based Thermal Assessment



Pixel-wise conditional U-Net with finite element-based transfer learning

including 4 steps:

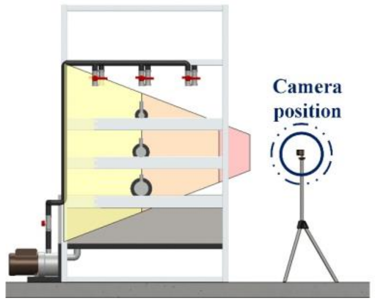
(1) dataset collection

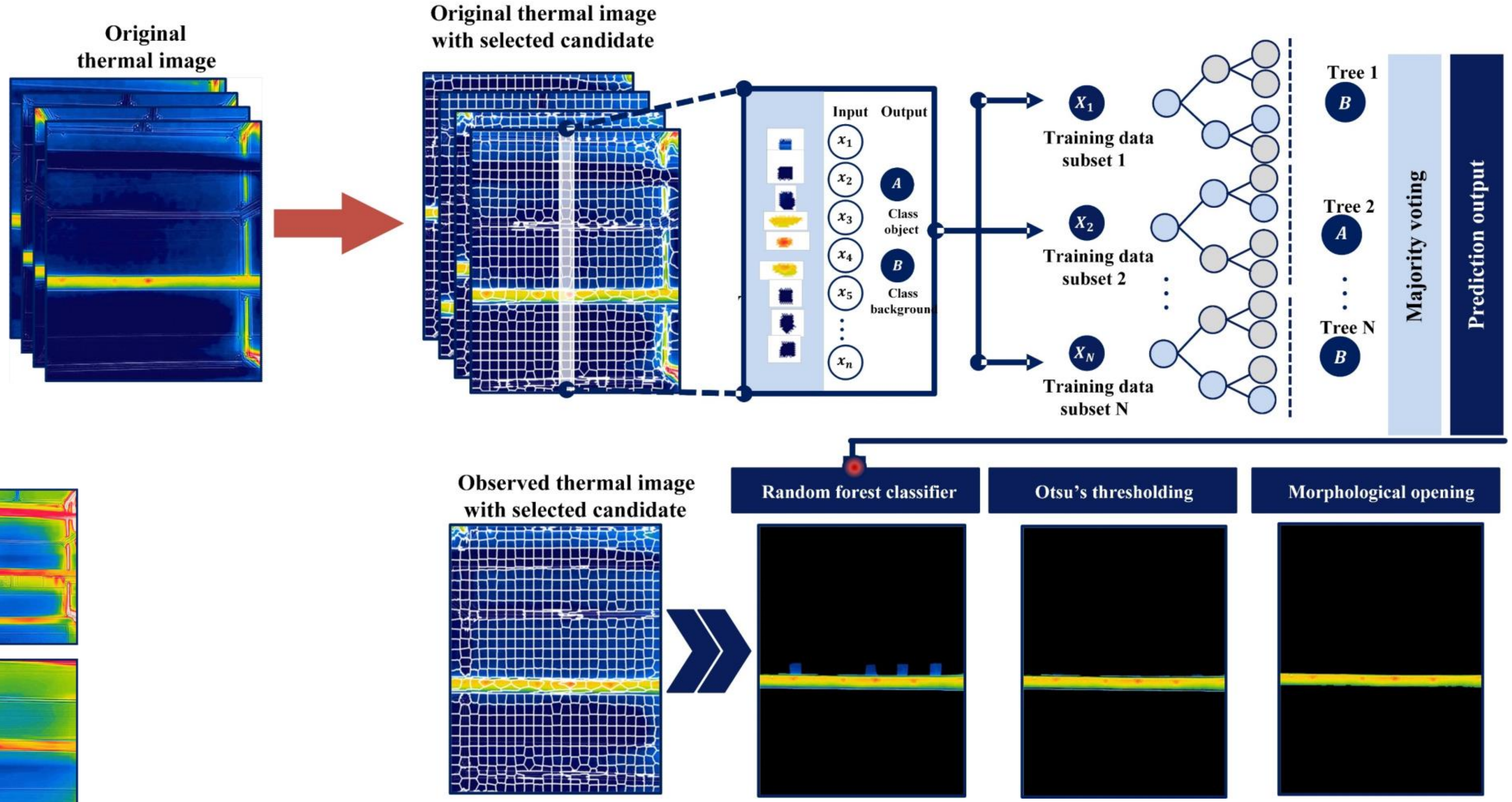
(2) pipe segmentation

(3) thermal pattern prediction

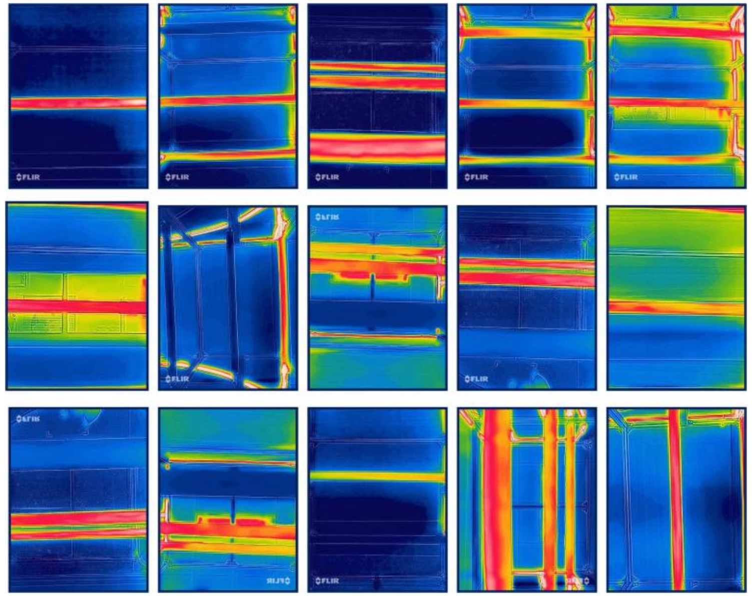
(4) relative heat-loss assessment

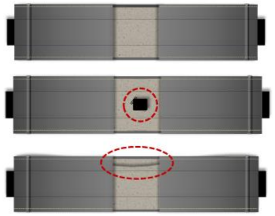
Thermal image segmentation: a bench-scale study





Experimental dataset





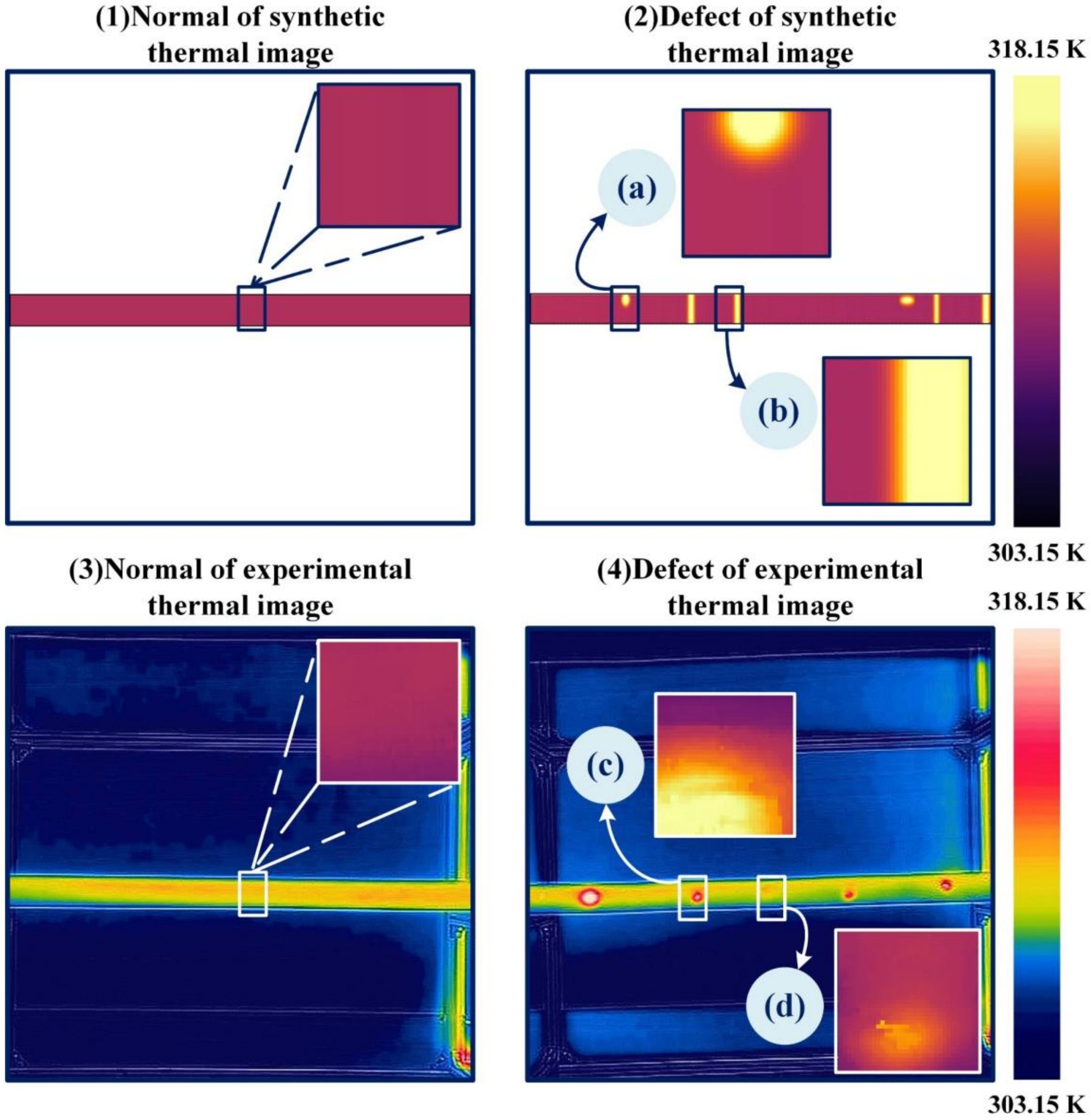
a) Normal Insulation

b) Damaged Insulation

c) Compressed Insulation

Superpixel-based pipe segmentation

Dataset visualization



Synthetic thermal image

(1) normal condition

(2a) elliptical defect

(2b) vertical-band defect

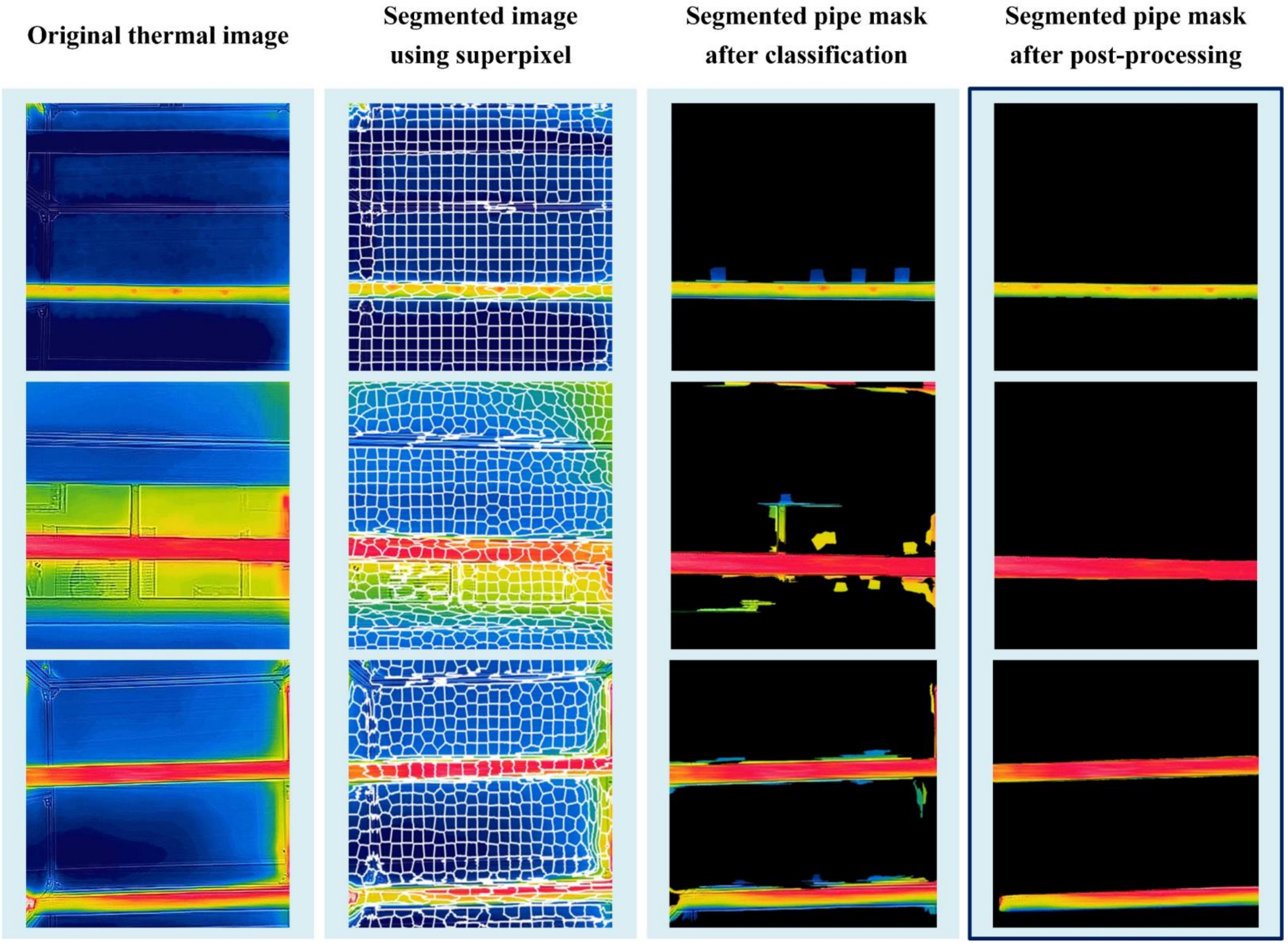
Experimental thermal image

(3) normal condition

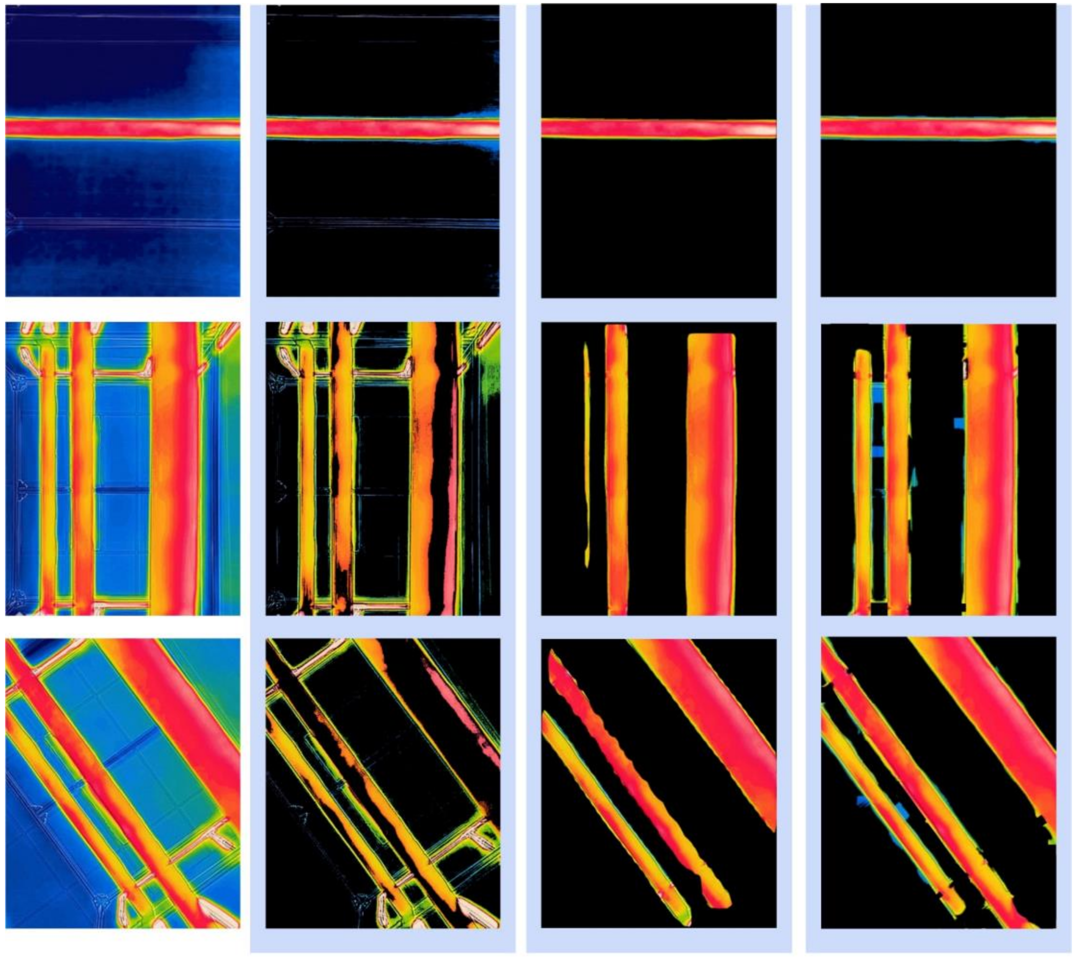
(4c) damaged insulation

(4d) compressed insulation

Pipe segmentation results



Pipe segmentation performance



Method	Segmentation accuracy			Pipe detection rate (%)	Processing per image (s.)
	PA	IoU	Dice		
Otsu's threshold	0.797	0.383	0.528	100	0.02
Mask R-CNN	0.954	0.739	0.781	85	0.45
Superpixel-based method	0.946	0.766	0.862	100	0.12

Pixel Accuracy (PA)

$$PA = \frac{Correct\ Pixels}{Total\ Pixels} \times 100\%$$

PA ↑ good overall segmentation

Intersection over Union (IoU)

$$IoU = \frac{Intersection}{Union} \times 100\%$$

IoU ↑ defect region closely matches actual location and size

Dice Coefficient (Dice, F1-score)

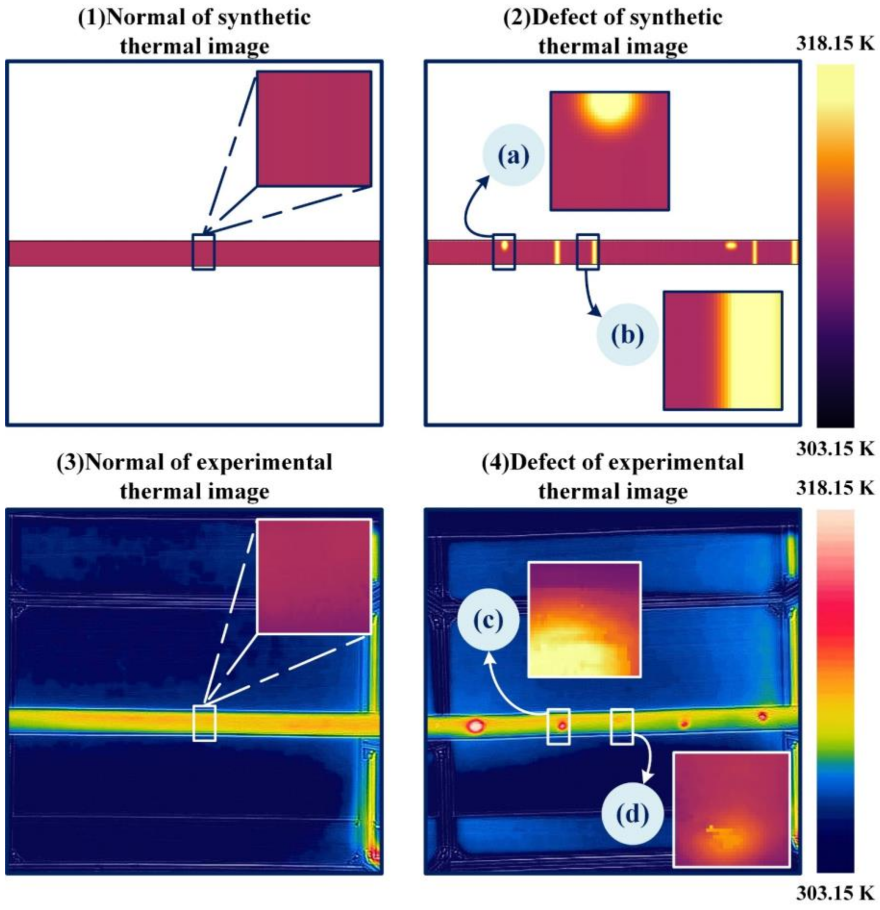
$$Dice = \frac{2(Intersection)}{(Prediction + Ground\ Truth)}$$

Dice ↑ Excellent segmentation quality

Conditional U-Net thermal pattern prediction

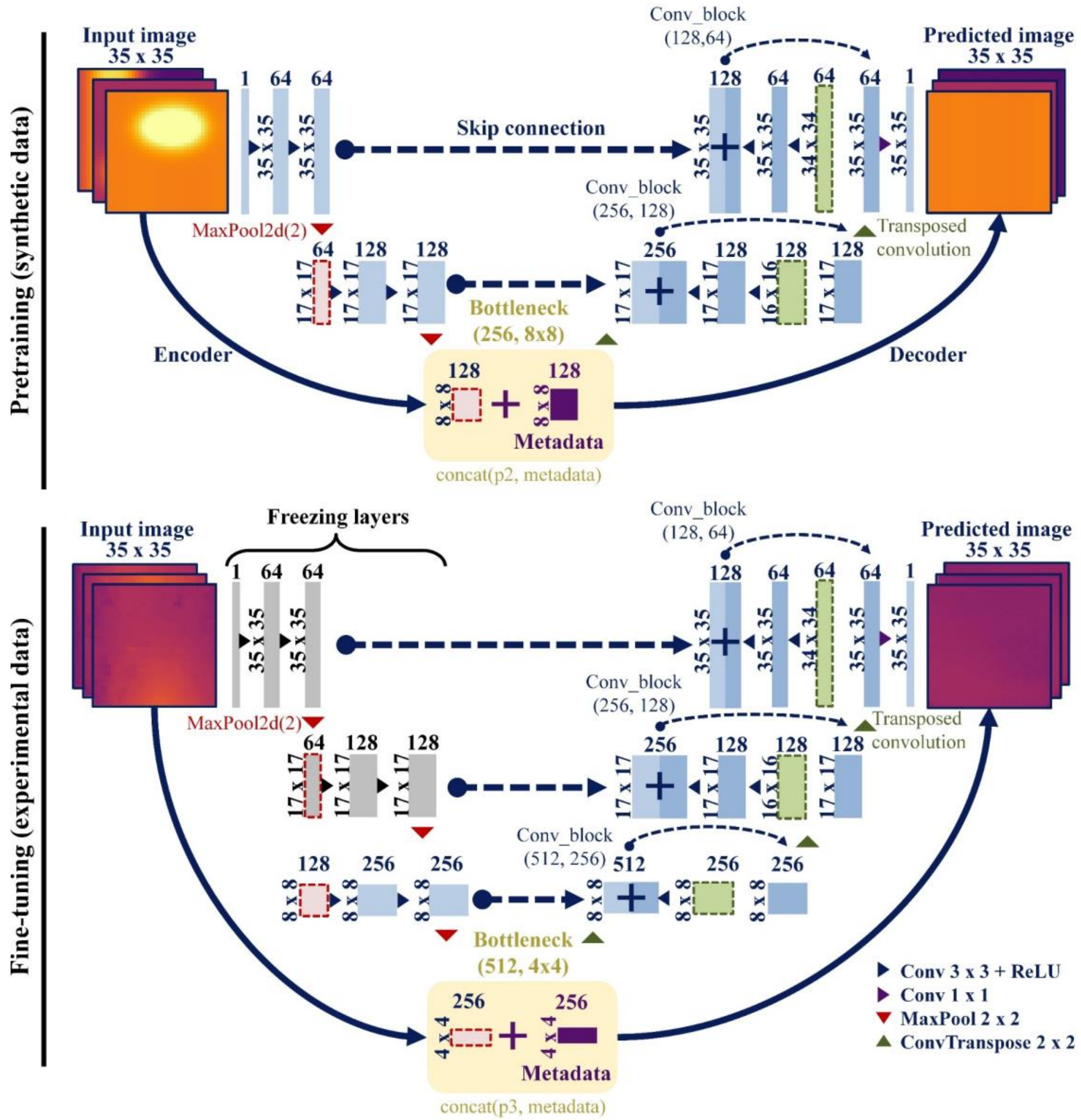
Pretraining process

210 Finite element-synthetic figures (outer surface T)



Fine-tuning process

84 Experimental figures



Heat-loss detection results

(a) Observed thermal image

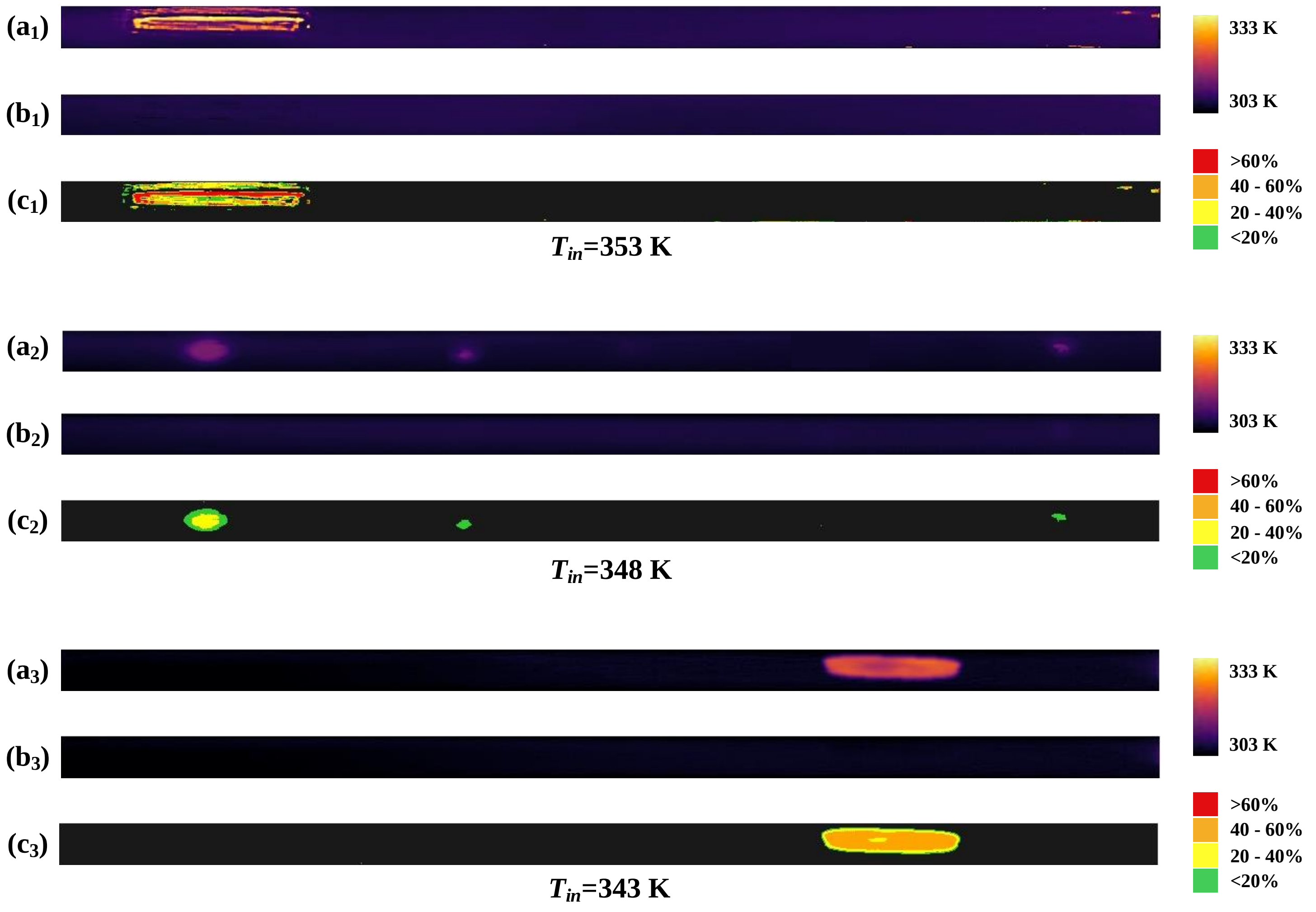
(b) Predicted normal baseline

(c) Residual map

(d) Color-coded map

Image of 1” pipe with 13 mm insulation thickness

Temperature-robust detection



1"pipe with 13 mm insulation thickness

(a) observed image

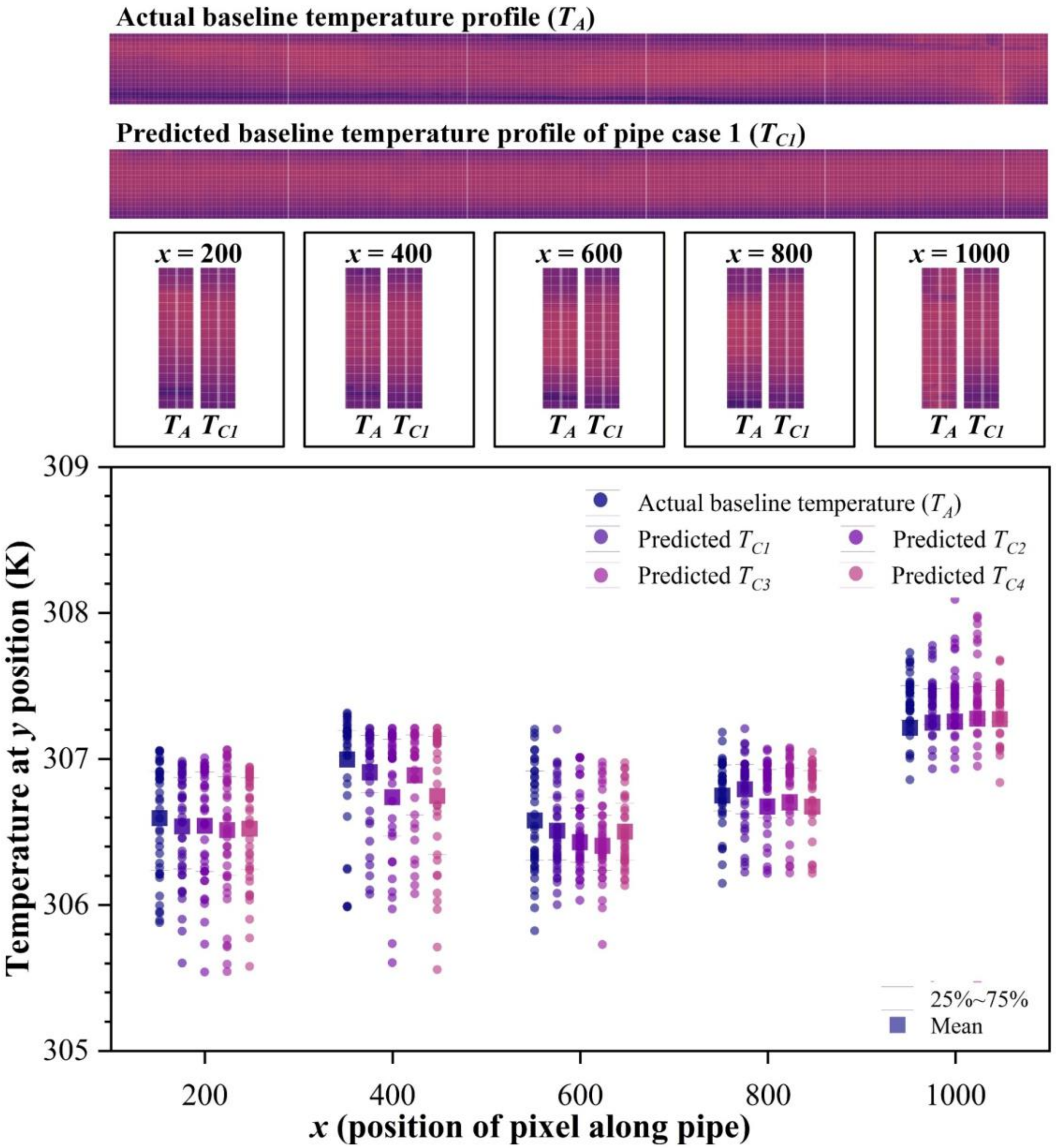
(b) Predicted baseline

(c) color-coded map

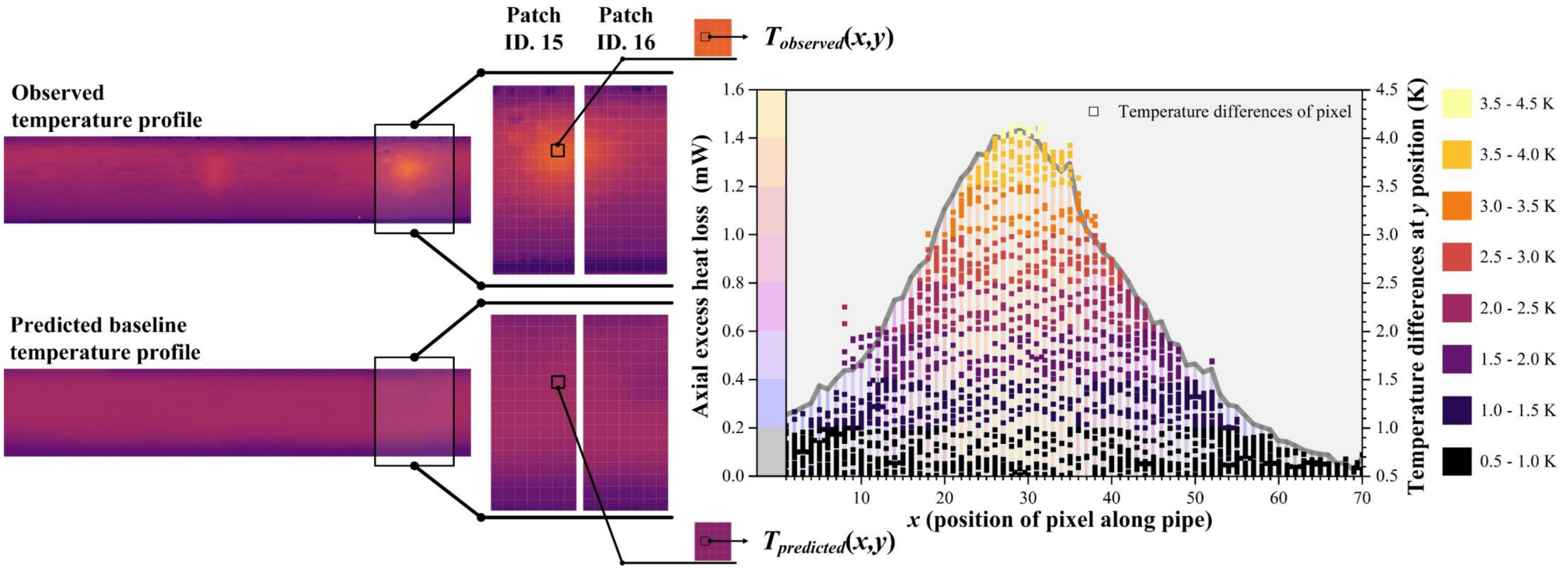
U-Net accuracy and computational efficiency

Patch size	Prediction accuracy			Computational cost	
	MAE	RMSE	R^2	Total training time (s)	Processing time (s)
15x15	0.009	0.012	0.913	3700.41	2.94
25x25	0.007	0.010	0.929	2533.31	2.23
35x35	0.008	0.011	0.928	2326.67	1.90

Actual & predicted baseline temperature profiles



Analysis of relative heat-loss quantification



Patch ID.	Number of defected pixels (pixel)	q ($W \cdot m^{-2}$)	Q_D (mW)
ID. 15-16	2,045	24.45	47

Area per pixel = 0.94 mm^2 Defect region = 1,922.3 mm^2

$$\Delta T(x,y) = T_{observed}(x,y) - T_{predicted}(x,y)$$

Radiation

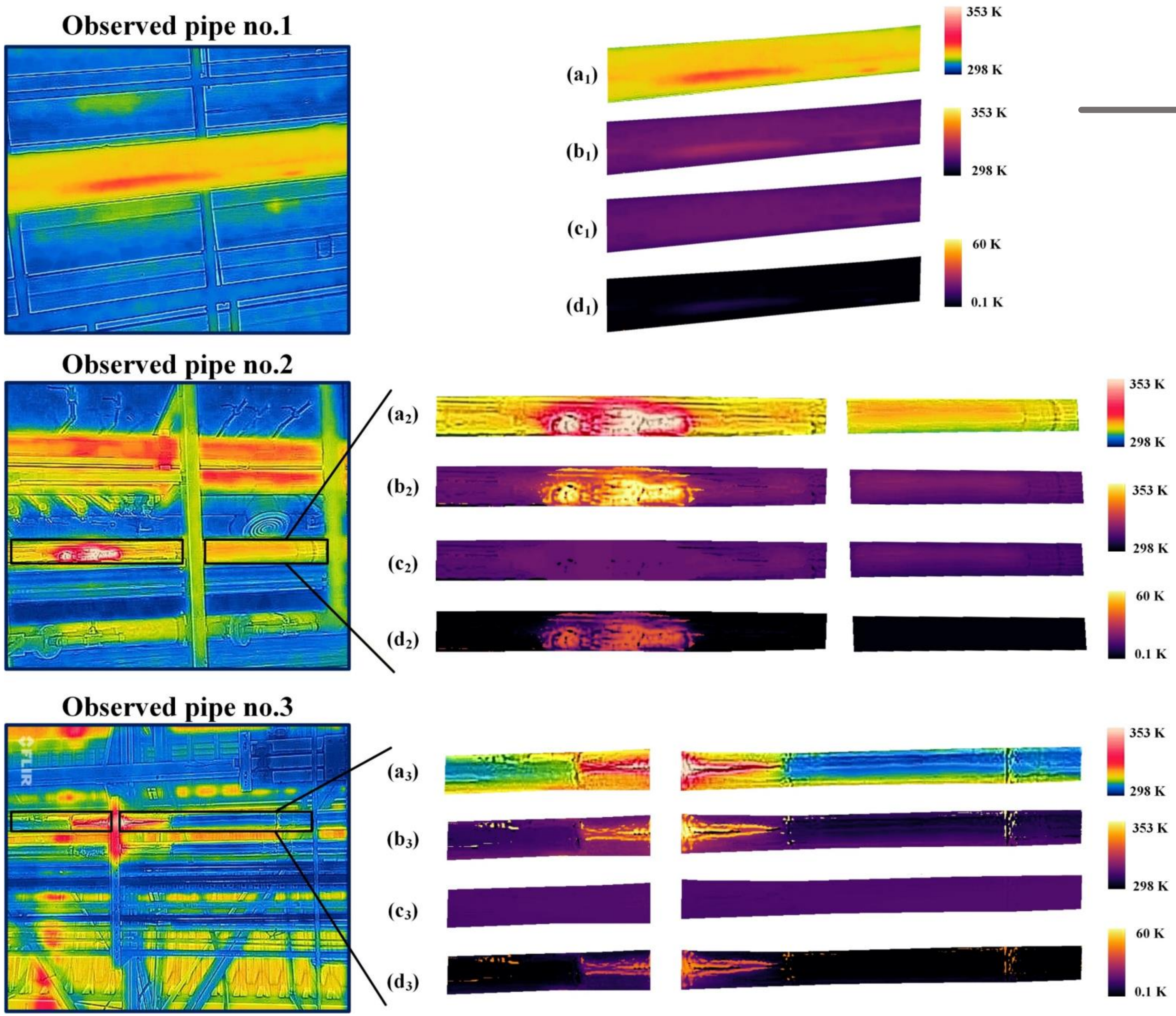
$$q(x,y) = \left[h\Delta T(x,y) + \varepsilon\sigma(T^4_{observed}(x,y) - T^4_{predicted}(x,y) \right] \cdot A_p$$

Convection

Pixel area

$$Q_D = \sum_{(x,y)\in D} \Delta q(x,y)$$

Heat-loss detection under industrial conditions



Pipe temperature profiles:

(a) observed pipe image with RGB colormap

(b) observed pipe image with inferno colormap

(c) predicted normal baseline by the conditional U-Net,

(d) pixel-wise residual map

Conclusion

- Proposed a thermal vision-based deep learning framework that effectively detects insulation defects and quantifies heat-loss in piping systems.
- Demonstrated strong performance in identifying compromised insulation areas with high accuracy under controlled conditions.
- Identified limitations in current methodology and field deployment.
- Future work focuses on model robustness, real-world validation, and practical implementation challenges.

Thank you