Infrared Image Recognition and Iterative Supervision (IIRIS)

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INTRODUCTION

The mitigation of residential and commercial energy loss requires rigorous structural energy audits. A substantial portion of latent energy loss occurs through the building envelope, primarily driven by compromised structural integrity, degrading insulation, thermal bridges, and unintended air infiltration.

Infrared thermography (IRT) is an established non-destructive testing (NDT) methodology. By capturing emitted infrared radiation, IRT visualizes heat transfer anomalies generally imperceptible to the naked eye. While effective radiometrically, manual interpretation of thermograms is subjective. Automated diagnostic frameworks leveraging computer vision offer a highly scalable alternative for rapid, standardized inspections.

- **Scalability:** Rapid, un-biased sub-pixel structural diagnostics suitable for massive portfolios.
- **Human-in-the-loop:** Bridging deep-learning researchers with civil engineers via targeted Active Learning tools.

DATASET & AUGMENTATION

A custom dataset of infrared thermograms was curated utilizing a FLIR A65 thermal camera equipped with a 640 × 512 focal plane array (FPA) microbolometer (accuracy: ±5 °C). Thermal footprints were captured locally at the University of Victoria.

24
ORIGINAL IMAGES

357
EXPERT POLYGONS

6
DIAGNOSTIC CLASSES

- **Anomaly Classes:** Thermal-Bridge, Missing Insulation, Air Leakage.
- **Structural Classes:** Window (reference), Spandrel, Vent.

To mitigate catastrophic overfitting across the initial 24 sample domains, the *Albumentations* library was employed to multiply the geometric variation by a factor of 10×, bringing the total corpus to 240 training-ready inputs. The pipeline generated artificial environmental shifts mapping horizontally flipped boundaries, ±15° camera rotation variances, and random contrast modulators.

METHODOLOGY & TRAINING

The **YOLOv11n-seg** (nano variant) model was selected for the segmentation inference plane. The v11 architecture utilizes Cross Stage Partial (CSP) networks combined with a robust Path Aggregation Network (PANet) for powerful multiscale feature fusion, critical for detecting diffuse thermal gradients at long-range focus limits.

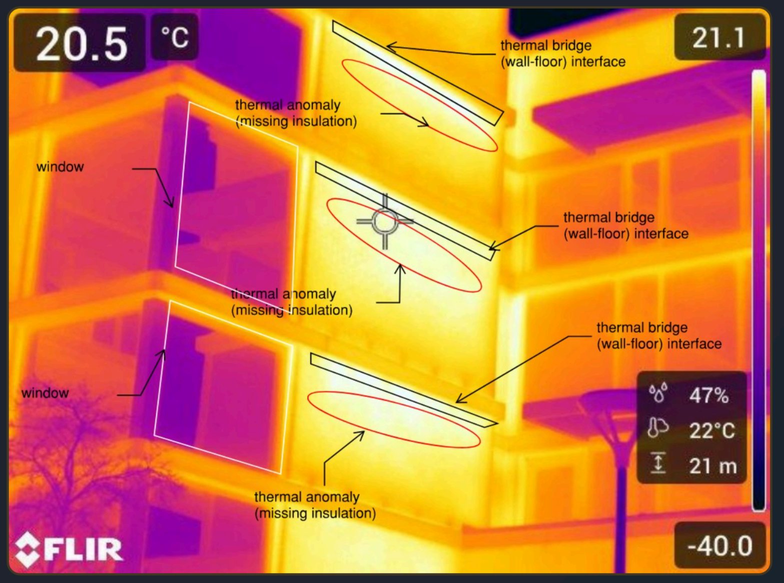
The network loss function evaluates a combination of Box Loss, Classification Loss (leveraging Focal weightings), and binary cross-entropy Segmentation Mask boundary logic.

Hyperparameter	Assigned Value
Base Input Resolution	640 × 640 matrices
Gradient Batch Size	32 Images
Training Limits	100 Epochs (Patience=20)
AdamW Bounds (lr0/lrf)	0.01 / 0.01
Loss Weights (box/cls/dfl)	7.5 / 0.5 / 1.5 weights
Overlap Boundaries	`overlap_mask=False`

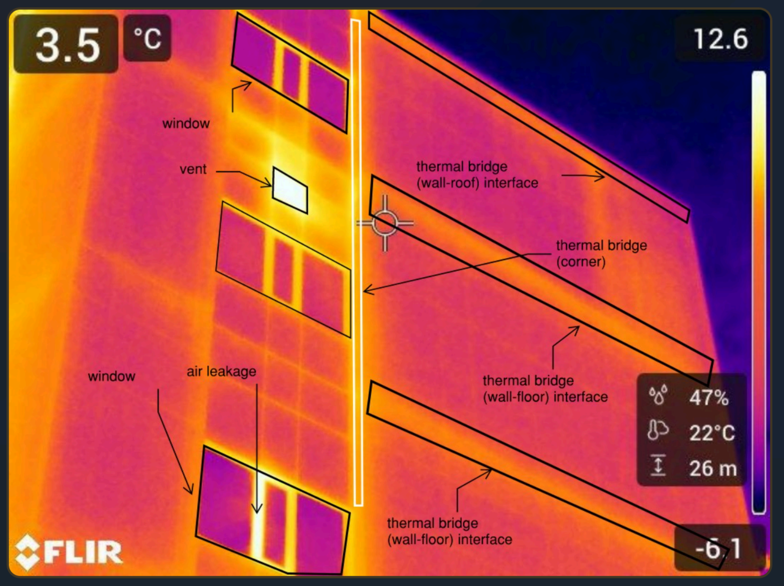
Because anomalies physically bleed into structural classes (e.g. cold air leaking directly off a pane window), the overlap bounding configuration allowed the model to delineate closely overlapping thermodynamic polygons cleanly.

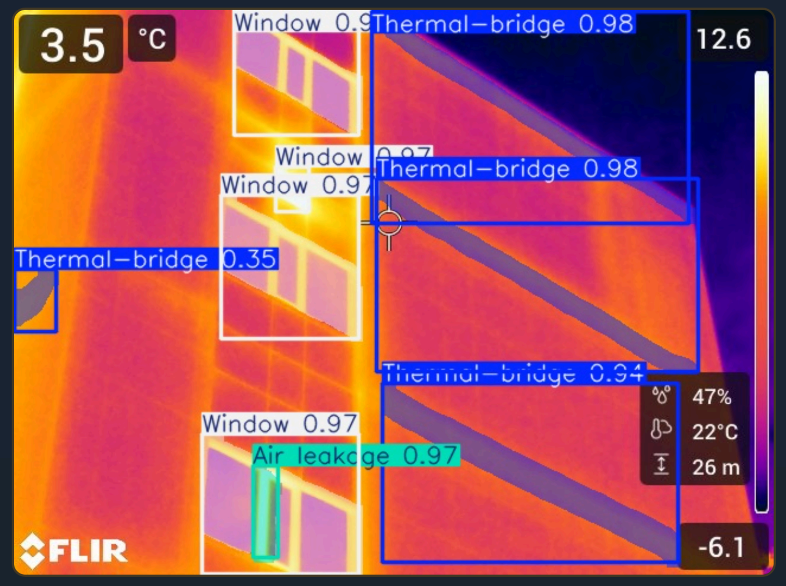
QUALITATIVE IMAGE COMPARISON

Visual inference evaluation between carefully manually plotted ground-truth structures against autonomous predictions rendered at an IoU boundary threshold of 0.50.


Ground Truth (IR_11489)

Prediction (IR_11489)


Ground Truth (IR_12079)



Prediction (IR_12079)

INTERACTIVE WEB FRAMEWORK

To transition findings from theoretical notebooks into practical civil engineering environments, a dedicated Flask-based web canvas was spun up. The interface incorporates real-time thermal inference mapped natively against manual human controls.


Autonomous Inference Module


Polygon "Active-Learning" Canvas

Significance: The Active-Learning module empowers certified energy auditors to manually adjust misaligned polygon boundaries on visually ambiguous images. These adjustments export natively to YOLO structures, facilitating rapid dataset retraining cycles directly from edge experts.

LIMITATIONS & FUTURE WORK

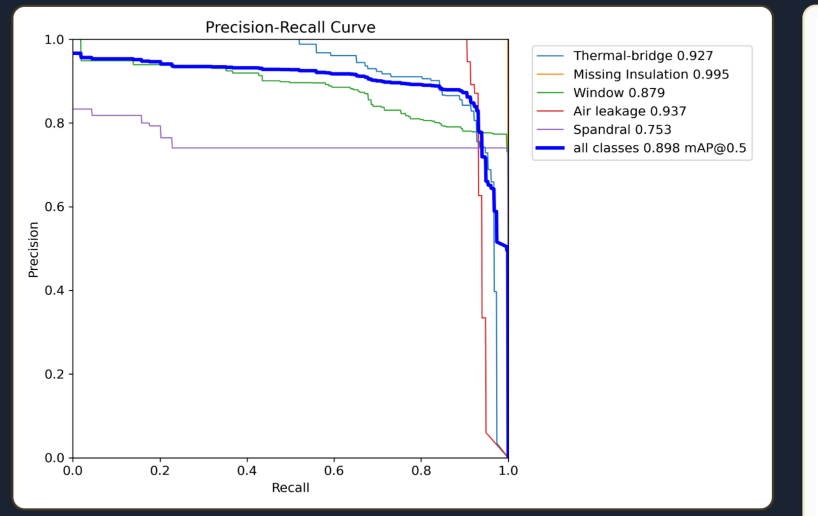
- **Geographic Restraints:** Base data derives exclusively from Pacific Northwest construction metrics inside the UVIC boundary. Performance remains untested in harsh freezing conditions.
- **UAV Deployment:** The nano-parameters dictate a direct pathway to translating this model natively via TensorRT limits directly onto drone cameras.

QUANTITATIVE DIAGNOSTIC METRICS

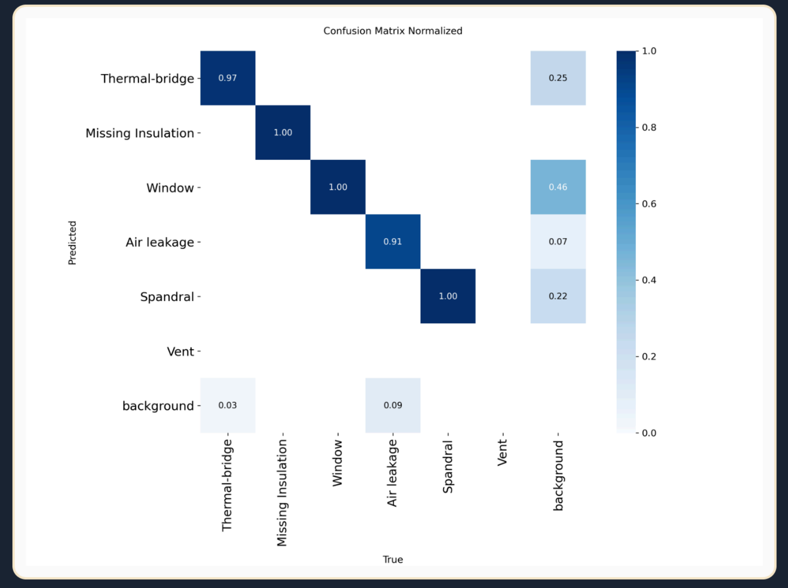
Evaluation against the 15% holdout validation boundary yielded incredibly high efficiency limits, proving lightweight networks can maintain phenomenal recall sensitivity against thermodynamic artifacts.

89.8%
MAP@50 OVERALL

95.8%
TOTAL RECALL VALUE



Precision-Recall Integration



Normalized Confusion Mapping

The high recall indicates a practically absolute low fraction of false negatives, a strictly mandatory parameter when assessing dangerous structural failure modes.

RIGOROUS VALIDATION PROTOCOLS

To eliminate concerns around dataset partition bias or over-optimization on highly specific data domains, the entire algorithmic setup was stress-tested across two advanced protocols:

1. Augmentation Disablement Ablation

Assessing performance on 24 unaugmented raw images exclusively.

- **mAP@50 Baseline:** 68.8% (↓21.0% Collapse)
- **Recall Baseline:** 84.1% (↓11.7% Collapse)

2. Full 5-Fold Cross Validation Array

Evaluating the framework linearly across 5 rotational cohort splits ensuring every image is tested precisely against varying parameters.

- **mAP@50 Standard:** 97.99% bounds (±0.52%)
- **Recall Standard:** 95.68% bounds (±1.39%)

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