

# YOLO Ensemble for UAV-based Multispectral Defect Detection in Wind Turbine Components

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Deep Learning

YOLOv8 + specialized thermal model

UAV Inspection

Multispectral data collection

Wind Turbines

Defect detection in blades, towers, motors

Performance

mAP@.5: 0.93 | F1-score: 0.90

# Abstract

## Research Overview

Enhanced defect detection in wind turbine components through **YOLO ensemble** integrating visible and thermal channels from UAV inspections. Combines general-purpose YOLOv8 with specialized thermal model using **bounding box fusion algorithm**, outperforming standalone models.

**0.93**

mAP@.5

**0.90**

F1-Score



### UAV Inspection

Advanced sensors enable monitoring of wind turbine blades, towers, and critical components



### Multispectral Fusion

Integration of RGB and thermal imagery for enhanced defect visibility



### YOLO Ensemble

Sophisticated fusion algorithm improves detection of both visual and thermal defects

# Introduction

## ⚠ Inspection Challenges

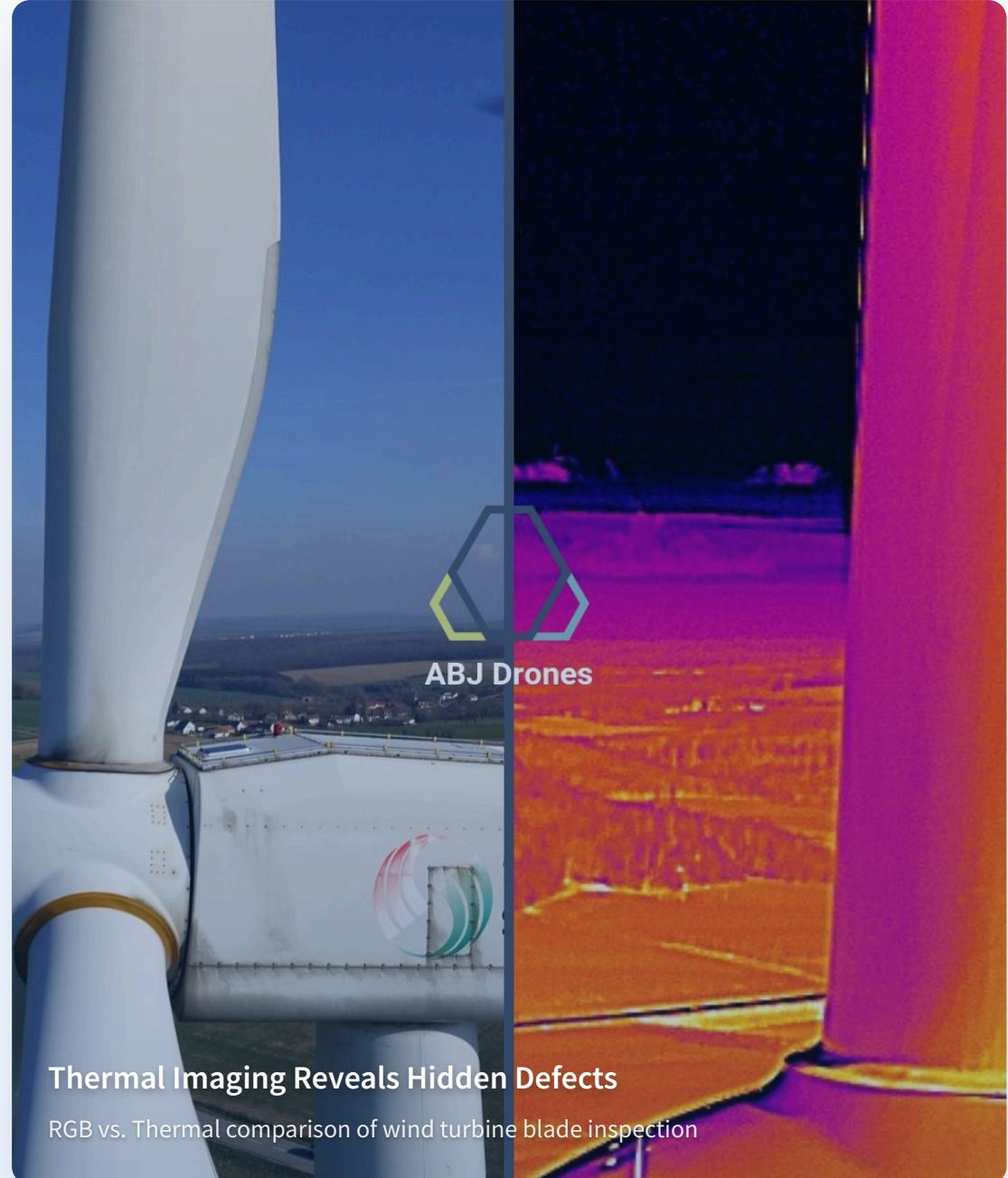
- Minor defects → **economic & safety risks**
- Timely maintenance → **efficiency & longevity**
- Complex geometries & remote locations

## 🚁 UAV-Based Inspection

- **High-resolution optical sensors** & thermal cameras
- Efficient data collection from multiple angles
- Captures defects invisible in RGB images

## ⚙ Data Processing

- Large data volumes → **real-time processing**
- Environmental conditions affect quality
- Robust algorithms for multispectral data



# Related Work



## Sensing Evolution

- › **RGB sensors** with basic ML
- › **Thermal cameras** for temperature anomalies
- › **Multispectral sensors** for early corrosion
- › **5G networks** & edge computing



## Algorithm Evolution

- › **Hand-crafted features** classifiers
- › **Deep learning** for defect patterns
- › **YOLO** for real-time detection
- › **Faster/Cascade R-CNN** for precision



## Fusion Evolution

- › **Simple averaging** of RGB & IR data
- › **CNN-based fusion** learning strategies
- › **Ensemble methods** combining detectors
- › **Research gap** in multispectral ensembles



## State-of-the-Art

✓ **Multispectral data** with advanced CNNs for reliable detection

✓ **Ensemble techniques** balance speed & accuracy for real-time inspection

✓ **RGB-IR fusion** effectively reduces missed defects

# Methodology Overview

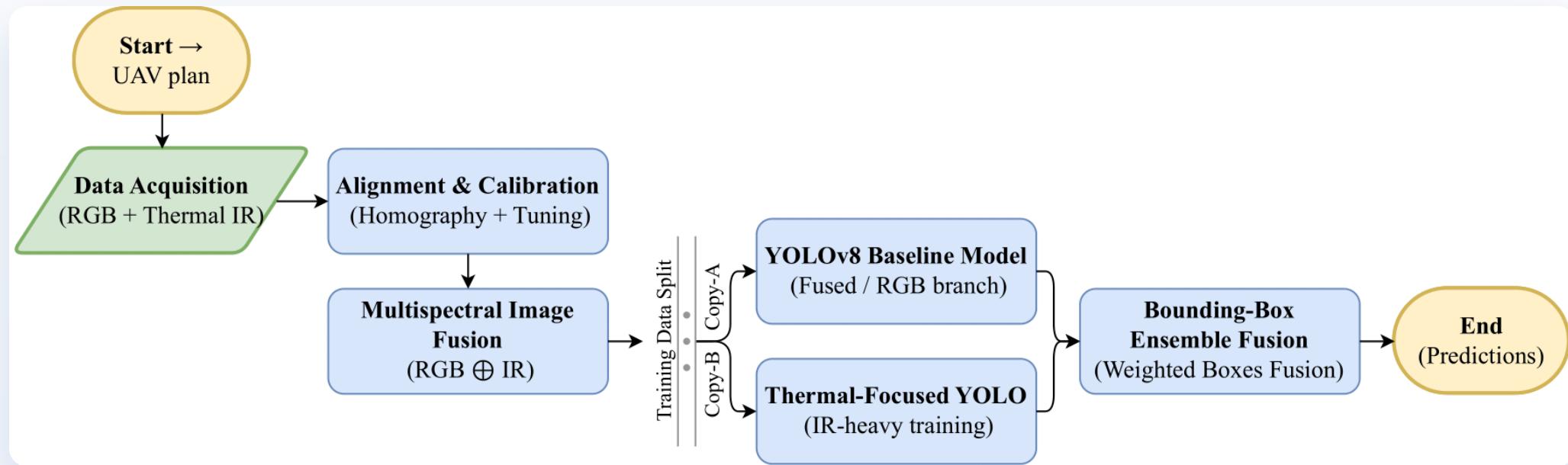


Figure 1: General workflow of our proposed ensemble approach



# Data Collection and Fusion



## RGB Channel

- ✓ **High-resolution** optical images (4K/6K)
- ✓ Detailed textural & color information
- ✓ Essential for **surface cracks** & corrosion



## IR Channel

- ✓ **Co-located infrared camera** capture
- ✓ Detects temperature-related anomalies
- ✓ Reveals **subsurface defects** invisible in RGB



## Multispectral Image Fusion

- 1 **Precise pixel-wise alignment** of IR to RGB
- 2 **Homography-based registration** for focal length differences
- 3 Fusion function: weighted sum to deep learning models (IFCNN)
- 4 Creates enriched representations for diverse defect detection

## Fusion Function

$$\text{Fusion}(x,y) = f(\text{RGB}(g_x(x,y), g_y(x,y)), \text{IR}(h_x(x,y), h_y(x,y)))$$

Where  $g_x$ ,  $g_y$  and  $h_x$ ,  $h_y$  represent geometric transformations applied to RGB and IR images, and  $f(\cdot, \cdot)$  is the fusion function

# YOLO Models



## YOLOv8 Baseline

- ✓ **High-speed inference** with state-of-the-art accuracy
- ✓ Ideal balance for **near real-time** UAV inspection
- ✓ Trained on both RGB and fused multispectral images



## Thermal Model (Mt)

- ✓ Exclusively trained on **IR-heavy data**
- ✓ Heightened sensitivity to subtle thermal gradients
- ✓ Detects defects often overlooked by general-purpose models



## Defect Classes



C1

### Cracks

Structural fractures compromising aerodynamic integrity

**Detection:** Visible surface fractures in blades, towers



C2

### Corrosion

Oxidative degradation on metallic surfaces

**Detection:** Primarily on tower and blade root connections



C3

### Overheating

Temperature anomalies indicating mechanical/electrical faults

**Detection:** Primarily via IR channel in nacelle components

# Ensemble Fusion Algorithm



## Bounding Box Fusion

- 1 Identify **overlapping boxes** of same class from both models
- 2 Calculate **weighted averages** of confidence & parameters
- 3 Create fused detection with combined information
- 4 Preserve unique findings from each model
- 5 Apply **Non-Maximum Suppression** to remove redundancies

## Weighted Average Formulas

$$P_{\text{ensemble}} = \gamma p_{M_t,j} + (1-\gamma)p_{y,i}$$

$$X_{\text{ensemble}} = \gamma x_{M_t,j} + (1-\gamma)x_{y,i}$$

$$Y_{\text{ensemble}} = \gamma y_{M_t,j} + (1-\gamma)y_{y,i}$$

$$W_{\text{ensemble}} = \gamma w_{M_t,j} + (1-\gamma)w_{y,i}$$

$$H_{\text{ensemble}} = \gamma h_{M_t,j} + (1-\gamma)h_{y,i}$$

Where  $\gamma \in [0, 1]$  controls the contribution of each model



### Weighting Factor

$\gamma = 0.5$  assigns equal importance to both models



### NMS Threshold

Removes boxes with IoU above threshold  $\tau_{\text{nms}}$

# Results - Performance Comparison



## YOLOv8 vs. Ensemble Performance

Defect Class	mAP@.5		mAP@.5:.95		Precision		F1-Score	
	YOLOv8	Ensemble	YOLOv8	Ensemble	YOLOv8	Ensemble	YOLOv8	Ensemble
Cracks (C1)	0.93	<b>0.95</b>	0.78	<b>0.81</b>	0.91	<b>0.93</b>	0.90	
Corrosion (C2)	0.90	<b>0.92</b>	0.75	<b>0.78</b>	0.88	<b>0.90</b>	0.87	
Overheating (C3)	0.89	<b>0.92</b>	0.74	<b>0.77</b>	0.87	<b>0.90</b>	0.86	
<b>Mean</b>	<b>0.91</b>	<b>0.93</b>	<b>0.76</b>	<b>0.79</b>	<b>0.89</b>	<b>0.91</b>	<b>0.88</b>	



## mAP@.5 Comparison



## F1-Score Comparison



### Overall Improvement

Ensemble achieves **+2.2%** mAP@.5 and **+3.9%** mAP@.5:.95 over single model



### Thermal Defects

Overheating detection shows **+3.4%** improvement in mAP@.5 with specialized model



### Balanced Performance

Ensemble maintains high precision while reducing false negatives across all defect types

# Results - State-of-the-Art Comparison

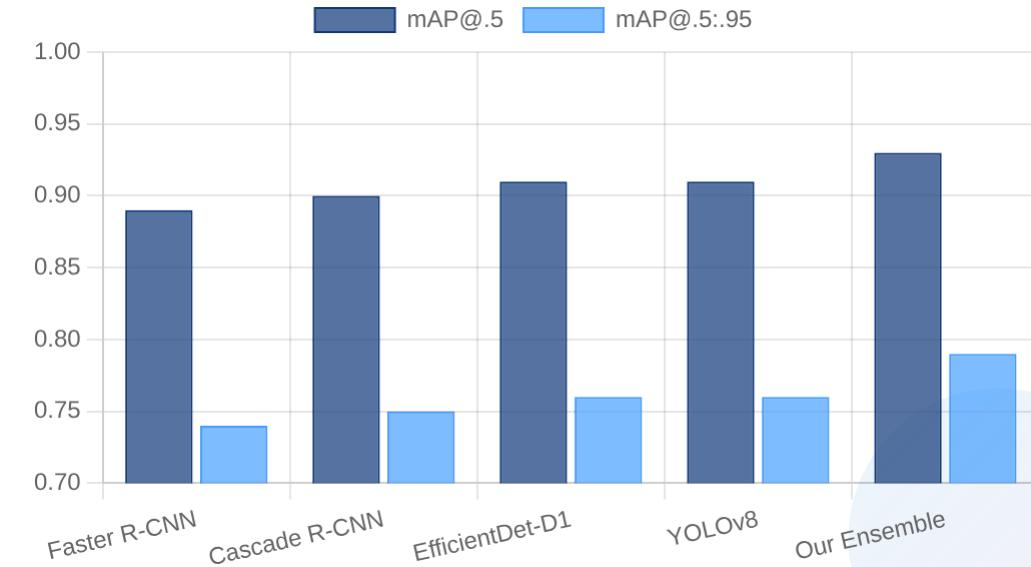


## Performance Comparison

Model	mAP@.5	mAP@.5:.95
Faster R-CNN	0.89	0.74
Cascade R-CNN	0.90	0.75
EfficientDet-D1	0.91	0.76
YOLOv8	0.91	0.76
<b>Our Ensemble</b> <span style="background-color: #e6f2ff; border: 1px solid #e6f2ff; padding: 2px 5px;">OURS</span>	<b>0.93</b>	<b>0.79</b>



## Visual Comparison



### Top Performance



Our ensemble achieves **highest mAP@.5 (0.93)** and **mAP@.5:.95 (0.79)** among all models



### Single-Stage Advantage

Single-stage detectors (YOLOv8, EfficientDet) outperform two-stage approaches in speed-accuracy balance

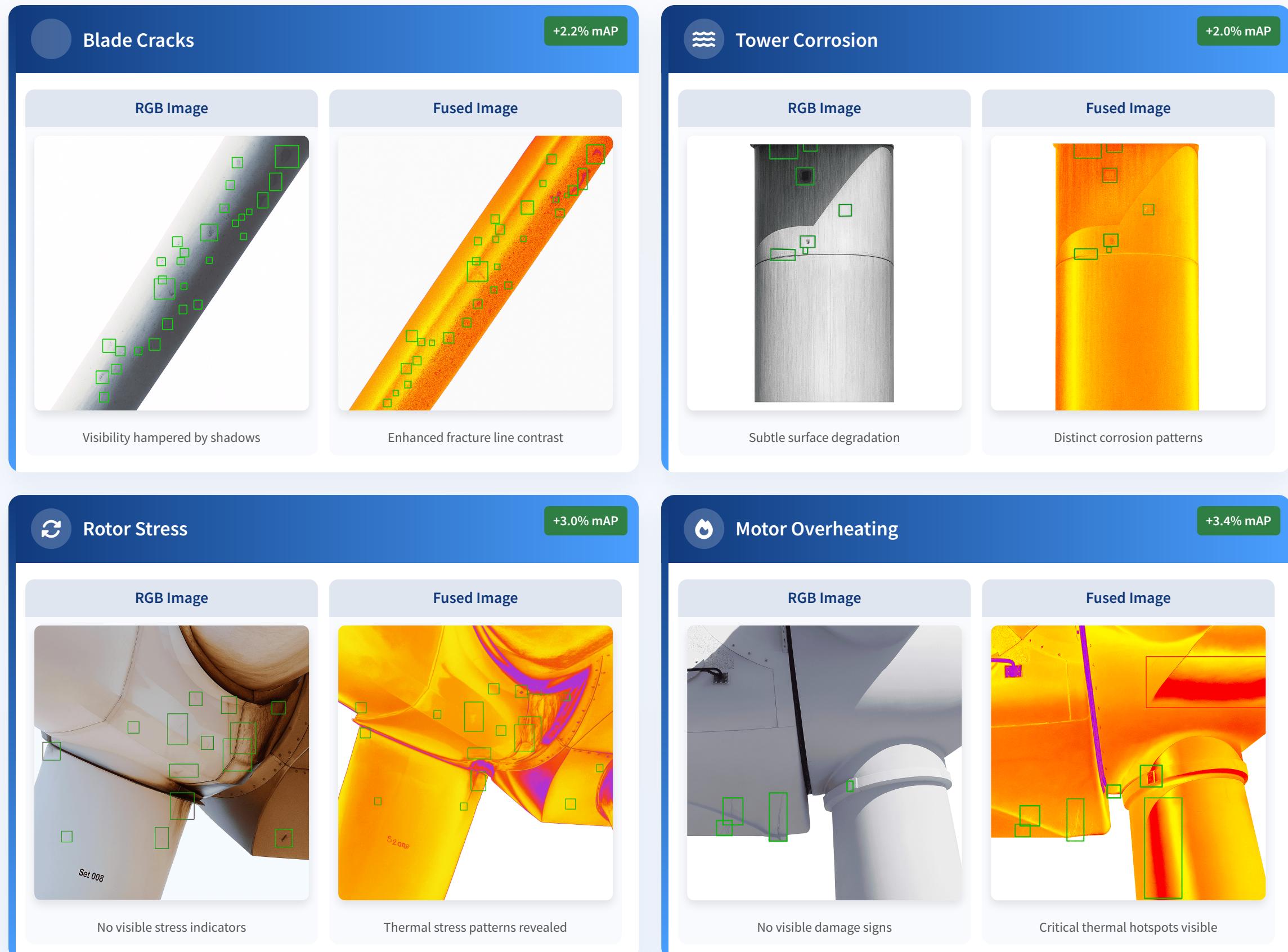


### Ensemble Benefits

Fusion of YOLOv8 with specialized thermal model provides **+3.9%** improvement in stricter mAP@.5:.95 metric

# Results - Qualitative Analysis

Comparison of RGB images vs. fused multispectral images demonstrates enhanced defect visibility



## Key Observations

**Enhanced contrast** improves surface defect detection

**Thermal anomalies** invisible in RGB revealed

**Critical defects** missed by visual inspection detected

# Conclusion and Future Work



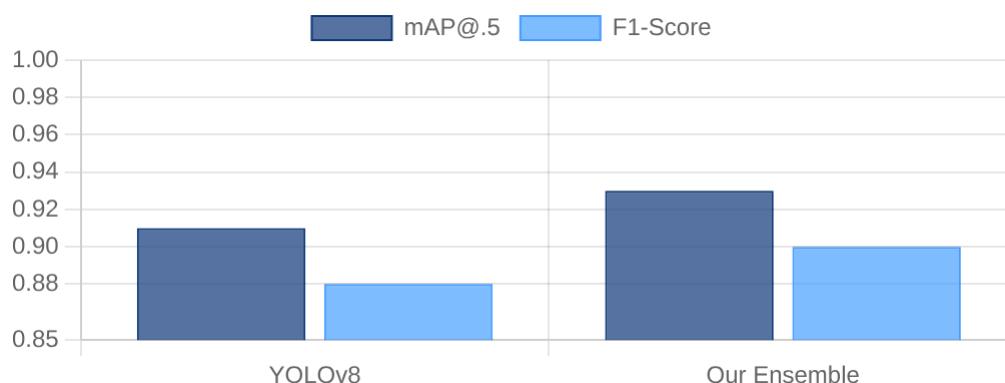
## Key Findings

↙ mAP@.5: 0.93 | F1-score: 0.90

↑ +2.2% improvement over single YOLOv8

🌡️ Superior **thermal defect** detection

🔍 Enhanced **subtle cracks** & **corrosion** visibility



0.93

mAP@.5

0.90

F1-Score



## Advantages

💡 **Multi-modal synergy** for comprehensive diagnostics

⚖️ **Speed** of single-stage + **precision** of specialist model

⚠️ Reduces **false negatives** & **false positives**

🎯 Addresses **single-spectral limitations**



## Future Research



### Edge deployment

optimization for UAVs



### Robust sensor fusion

algorithms



### Environmental noise

reduction



### Hyperspectral imaging

integration

0.93

mAP@.5

0.90

F1-Score

+2.2%

Improvement

3

Defect Types