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

Serhii Svystun, Pavlo Radiuk, Oleksandr Melnychenko, Oleg Savenko, Anatoliy Sachenko

The 13th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications

4-6 September, 2025, Gliwice, Poland

Abstract

This research enhances defect detection accuracy in wind turbine components through an **ensemble of YOLO-based deep learning models** that integrate visible and thermal channels from UAV inspections. Our approach combines a general-purpose YOLOv8 model with a specialized thermal model using a sophisticated bounding box fusion algorithm, achieving a **mean Average Precision (mAP@.5) of 0.93** and an F1-score of 0.90, outperforming standalone YOLOv8.

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

Wind Turbine Inspection Challenges

- Minor defects can lead to **substantial economic and safety risks**
- Timely maintenance is critical for **efficiency and longevity**
- Complex geometries and remote locations complicate inspection

UAV-Based Inspection

- Equipped with **high-resolution optical sensors** and thermal cameras
- Efficiently collect visual information from multiple angles
- Capture subtle or internal defects not visible in RGB images

Data Processing Challenges

- Large amounts of data require **real-time processing**
- Environmental conditions affect data quality
- Need for robust algorithms to analyze multispectral data

Related Work

Evolution of Sensing

- Early methods: **Conventional RGB sensors** with basic machine learning
- Modern UAVs: Integration of **thermal (IR) cameras** to detect temperature anomalies
- Advanced systems: **Multispectral sensors** for identifying early-stage corrosion
- Infrastructure: Adoption of **5G networks** and edge computing architectures

Evolution of Algorithms

- Early approaches: **Classifiers with hand-crafted features**
- Modern methods: **Deep learning models** that automatically learn hierarchical defect patterns
- Real-time detectors: **YOLO** offering speed advantages
- High-precision detectors: **Faster R-CNN, Cascade R-CNN** providing higher accuracy

Evolution of Fusion

- Basic techniques: **Simple averaging** of RGB and IR data
- Advanced approaches: **CNN-based fusion** learning optimal strategies
- Ensemble methods: **Combining fast detectors** with precise models
- Research gap: Limited focus on **ensemble learning** with multispectral data

Current State-of-the-Art

- **Multispectral data** with advanced CNN architectures is key to reliable defect detection
- **Ensemble techniques** balance speed and accuracy for real-time inspection
- **RGB-IR fusion** effectively reduces missed defects in challenging conditions

Methodology Overview

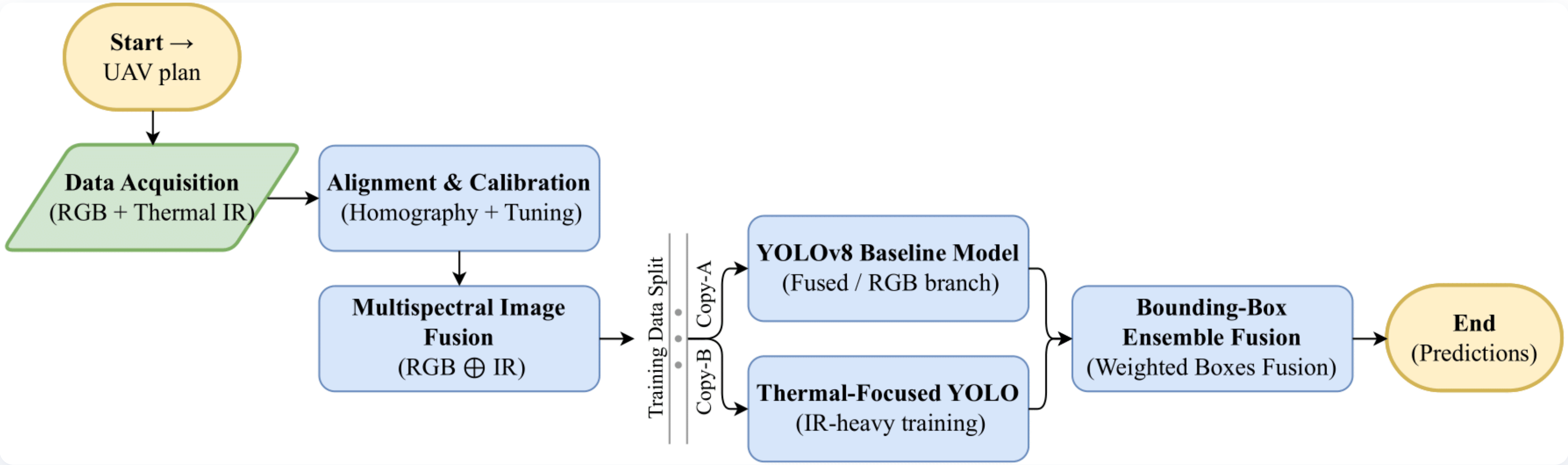


Figure 1: General workflow of our proposed ensemble approach

Data Acquisition

UAVs capture **RGB** and **thermal IR** imagery of wind turbine components

Multispectral Fusion

Precise alignment and fusion of RGB and IR data using **homography-based registration**

Parallel Model Training

Training **baseline YOLOv8** and **specialized thermal model** on fused data

Ensemble Fusion

Combining predictions using **weighted bounding-box fusion** algorithm

Data Collection and Fusion

RGB Channel

- **High-resolution** optical images (4K or 6K)
- Detailed textural and color information
- Essential for identifying **surface cracks** and corrosion

IR Channel

- Captured using **co-located infrared camera**
- Detects temperature-related anomalies
- Reveals **subsurface defects** invisible in RGB spectrum

Multispectral Image Fusion

1. **Precise pixel-wise alignment** of IR channel to corresponding RGB image
2. **Homography-based registration** technique accounts for focal length differences and spatial offsets
3. Fusion function ranges from simple weighted sum to sophisticated deep learning models (e.g., IFCNN)
4. Creates enriched image representations that enhance visibility of diverse defect types

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 Model

- **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

Specialized 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

Cracks (C1)

Structural fractures compromising aerodynamic integrity

Detection: Visible surface fractures in blades, towers

Corrosion (C2)

Oxidative degradation on metallic surfaces

Detection: Primarily on tower and blade root connections

Overheating (C3)

Temperature anomalies indicating mechanical or electrical faults

Detection: Primarily via IR channel in nacelle components

Ensemble Fusion Algorithm

Bounding Box Fusion

1. Identify **overlapping bounding boxes** of the same class from both models
2. Calculate **weighted averages** of confidence scores and box parameters
3. Create fused detection with combined information
4. Preserve unique findings from each model
5. Apply **Non-Maximum Suppression** to remove redundant detections

Weighted Average Formulas

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

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

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

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

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

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 predefined threshold τ_{nms}

Results - Performance Comparison

Single 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	**0.95**	0.78	**0.81**	0.91	**0.93**	0.90	**0.92**
Corrosion (C2)	0.90	**0.92**	0.75	**0.78**	0.88	**0.90**	0.87	**0.89**
Overheating (C3)	0.89	**0.92**	0.74	**0.77**	0.87	**0.90**	0.86	**0.89**
Mean	0.91	**0.93**	0.76	**0.79**	0.89	**0.91**	0.88	**0.90**

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 with Established Models

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 (Single Model)	0.91	0.76
Our Ensemble (YOLOv8 + Mt)	**0.93**	**0.79**

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

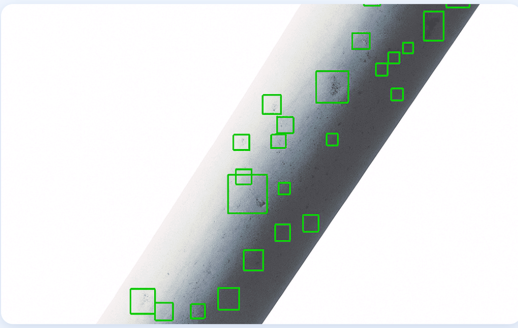
Fusion of YOLOv8 with specialized thermal model provides **+3.9%** improvement in stricter mAP@.5:.95 metric

Results - Qualitative Analysis

Comparison of defect detection in **RGB images** vs. **fused multispectral images** demonstrates the enhanced visibility of defects through our approach

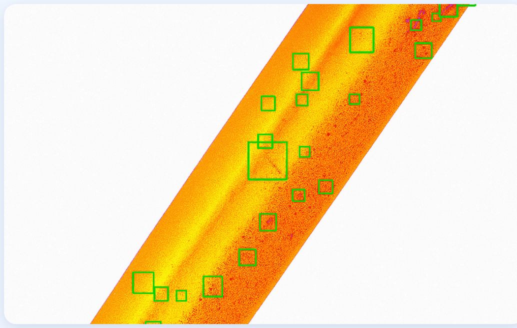
Blade Cracks

RGB Image



Crack visibility hampered by shadows and surface texture

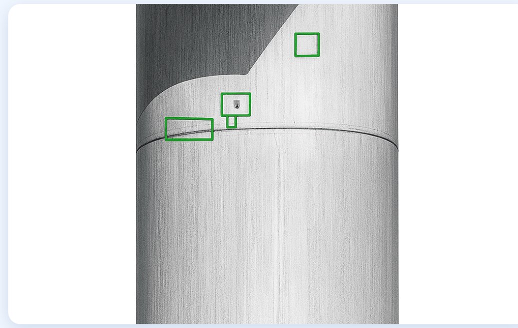
Fused Image



Enhanced contrast along fracture line improves detection

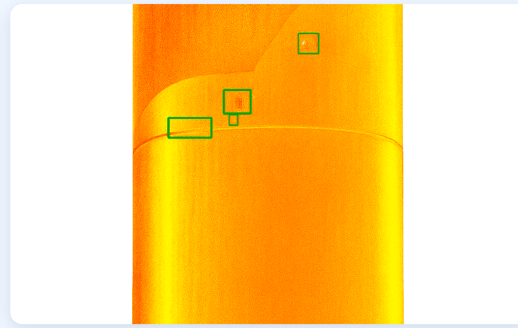
Tower Corrosion

RGB Image



Subtle surface degradation difficult to distinguish

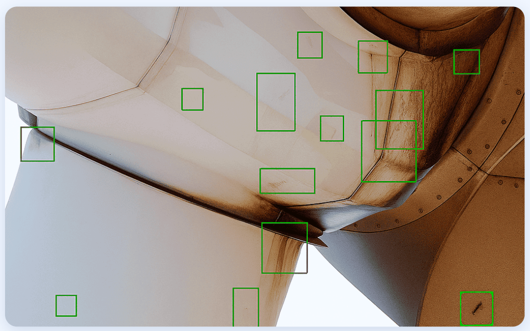
Fused Image



Corrosion made more distinct against background

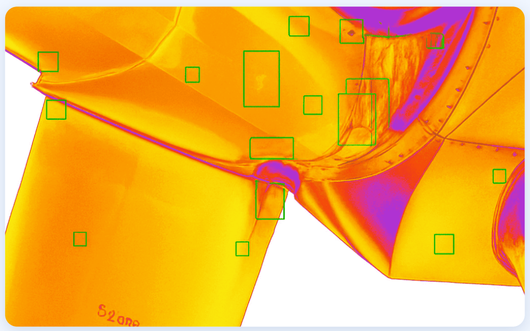
Rotor Stress

RGB Image



No visible signs of structural stress

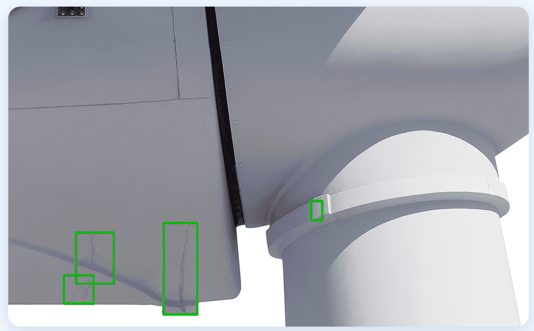
Fused Image



Thermal patterns reveal potential stress points

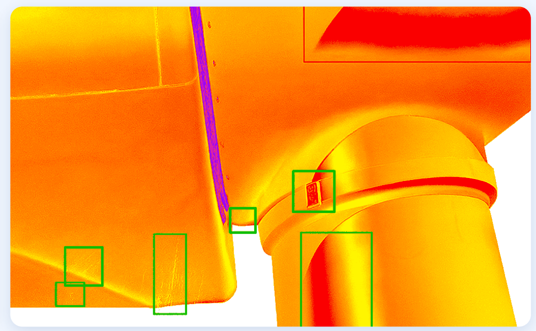
Motor Overheating

RGB Image



No obvious signs of damage visible

Fused Image



Critical thermal hotspots clearly revealed

Key Observations

- **Enhanced contrast** improves detection of visible surface defects
- **Thermal anomalies** invisible in RGB spectrum are revealed
- **Critical defects** missed by visual inspection are detected

Conclusion and Future Work

Key Findings

- Ensemble approach achieves **mAP@.5 of 0.93** and **F1-score of 0.90**
- **2.2% improvement** over single YOLOv8 model
- Superior detection of **thermal defects** invisible in RGB spectrum
- Enhanced visibility of **subtle cracks** and **corrosion**

Advantages

- **Multi-modal synergy** provides comprehensive diagnostic tool
- Combines **speed of single-stage** with **precision of specialist model**
- Reduces both **false negatives** and **false positives**
- Addresses limitations of **single-spectral approaches**

Future Research Directions

- Optimize ensemble for **real-time edge deployment** on computationally constrained UAVs
- Develop more **robust sensor fusion algorithms** to mitigate alignment challenges
- Reduce **environmental noise sensitivity** in thermal data processing
- Incorporate **additional data modalities** like hyperspectral imaging

0.93	0.90	+2.2%	3
mAP@.5	F1-Score	Improvement	Defect Types