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

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Abstract

Research Focus

UAVs with advanced sensors for wind turbine monitoring, integrating **visible and thermal channels** for enhanced defect detection

Methodology

- Ensemble of YOLO-based deep learning models
- Integration of RGB and thermal IR data
- Sophisticated bounding box fusion algorithm

Key Findings

- Outperforms standalone YOLOv8 model
- Enhanced detection of both visual and thermal defects
- More reliable solution for wind turbine inspection

0.93
mAP@.5

0.90
F1-Score

+2.2% improvement over single model

Reliable multispectral defect detection

Introduction

Wind Power in Energy Transition

Wind power plants play a **critical role** in the global transition to renewable energy

Maintenance Importance

- Efficiency and longevity depend on **timely maintenance**
- Undetected defects pose substantial economic and safety risks

UAV Inspection Capabilities

- High-resolution optical sensors and thermal cameras
- Capture subtle or internal defects not visible in standard RGB

Key Challenges

- Processing large amounts of data in real-time
- Environmental conditions (wind, glare, shadows)
- Need for robust, intelligent algorithms

Related Work

Evolution of UAV Inspection

1. Conventional RGB sensors + basic ML
2. **Thermal (IR) cameras** for temperature anomalies
3. Multispectral sensors for early-stage corrosion

Data Fusion Techniques

→ From simple averaging to **advanced CNNs**

→ Learning optimal fusion strategies automatically

Detection Algorithms

→ From hand-crafted features to **deep learning**

→ Real-time detectors (YOLO) vs. accurate two-stage (Faster R-CNN)

Ensemble Techniques

→ Combining fast detectors with precise models

→ RGB-IR fusion reduces missed defects in challenging conditions

! Research Gap

Existing studies focus on single detection models or single spectral range, omitting potential benefits of ensemble learning with multispectral data

Methodology Overview

Our approach leverages **complementary strengths** of multispectral imagery by integrating high-resolution visible (RGB) and thermal (IR) data channels through an ensemble of YOLO-based models.

1. **Data Acquisition**
   RGB + Thermal IR imagery
2. **Alignment & Calibration**
   Homography + Tuning
3. **Multispectral Fusion**
   RGB ⊕ IR integration
4. **Parallel Model Training**
   YOLOv8 + Thermal-Focused Model
5. **Ensemble Fusion**
   Weighted Boxes Fusion

Figure 1: General workflow of our proposed ensemble approach. The process involves aligning and fusing RGB and IR data, training models in parallel, and combining predictions.

Data Collection & Multispectral Fusion

RGB Channel

- **High-resolution** optical images (4K/6K)
- Detailed textural and color information
- Identifies surface cracks and corrosion

IR Channel

- **Thermal images** from co-located camera
- Detects temperature-related anomalies
- Reveals defects invisible in RGB spectrum

Multispectral Image Fusion

- **Precise pixel-wise alignment** using homography-based registration
- Accounts for differences in focal lengths and spatial offsets
- Fusion function ranges from simple weighted sum to sophisticated deep learning models (IFCNN)

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

YOLOv8 Model & Specialized Model

YOLOv8 Baseline

- **Balance** of high-speed inference and accuracy
- Trained on RGB and fused multispectral images
- Ideal for near real-time UAV inspection

Thermal Model (Mt)

- **Specialized** for thermal anomaly detection
- Heightened sensitivity to subtle thermal gradients
- Trained exclusively on IR-heavy data

Critical Defect Classes

Cracks

C1

Structural fractures compromising aerodynamic integrity

Corrosion

C2

Oxidative degradation on metallic surfaces

Overheating

C3

Temperature anomalies indicating mechanical/electrical faults

Ensemble Fusion Algorithm

Bounding Box Fusion

- Combines predictions from **baseline YOLOv8** and **specialized thermal model**
- Model outputs: $O_y = \{D_{y,i} = (c_{y,i}, b_{y,i}, p_{y,i})\}$ and $O_{Mt} = \{D_{Mt,j} = (c_{Mt,j}, b_{Mt,j}, p_{Mt,j})\}$
- Weighting factor $\gamma \in [0,1]$ controls contribution of each model
- Final post-processing: **Non-Maximum Suppression (NMS)**

Bounding box fusion visualization

Fusion Equations

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

Algorithm 1: Key Steps

1. Find overlapping detections of same class with IoU $\geq \tau_{iou}$
2. Create fused detection using weighted averages
3. Combine fused and unmerged detections
4. Apply NMS with threshold τ_{nms} to produce final set

Results: Single Model vs. Ensemble

Comparative Performance Metrics

Defect Class	mAP@.5		F1-Score	
	YOLOv8	Ensemble	YOLOv8	Ensemble
Cracks (C1)	0.93	**0.95**	0.90	**0.92**
Corrosion (C2)	0.90	**0.92**	0.87	**0.89**
Overheating (C3)	0.89	**0.92**	0.86	**0.89**
Mean	**0.91**	0.93	**0.88**	0.90

Table I: Comparative Performance of Single YOLOv8 Model vs. Proposed Ensemble

Key Improvements

Mean mAP@.5	+2.2%	↑
Mean mAP@.5:.95	+3.9%	↑
Mean F1-score	+2.3%	↑

Key Findings

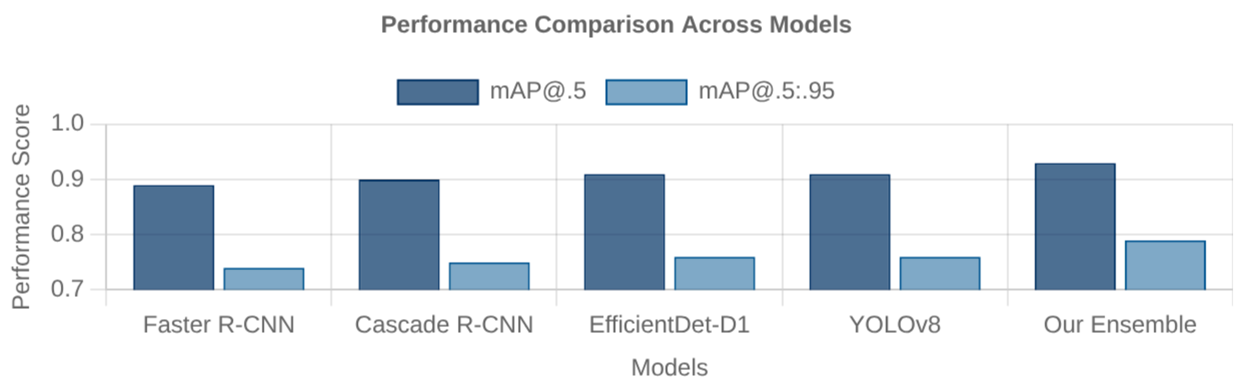
- Ensemble approach reduces both false negatives and false positives
- Most significant improvement in detecting thermal anomalies (Overheating)
- Enhanced robustness and reliability for wind turbine inspection

Results: Comparison with State-of-the-Art

Comparative Performance Metrics

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)	0.91	0.76
Our Ensemble Best	**0.93**	**0.79**

Table II: Comparative Performance with State-of-the-Art Models



Key Observations

- Proposed ensemble **surpassed all other models** in both metrics
- Single-stage models (YOLOv8, EfficientDet) outperform two-stage detectors
- Largest improvement in stricter mAP@.5:.95 metric (+3.9%)

Conclusion

- Ensemble capitalizes on YOLOv8's feature extraction power
- Specialized thermal model enhances detection of subtle thermal signatures
- Optimal balance of speed and accuracy for UAV inspection

Results: Qualitative Analysis

Visual comparison demonstrates how multispectral fusion enhances defect detection across key wind turbine components

Blade Crack (RGB)

Visibility hampered by shadows and surface texture

Blade Crack (Fused)

Enhanced contrast along fracture line

Tower Corrosion (RGB)

Subtle surface degradation less visible

Tower Corrosion (Fused)

Improved detection of corrosion patterns

Rotor Hub (RGB)

Appears unremarkable in standard imagery

Rotor Hub (Fused)

Reveals **thermal patterns** indicating stress

Motor Component (RGB)

No obvious signs of damage visible

Motor Component (Fused)

Clearly reveals **critical thermal hotspots**

Key Findings

- Enhanced detection of visible surface defects through improved contrast
- Identification of non-visible thermal anomalies critical for maintenance
- System excels at detecting defects missed by standard RGB inspection

Figure 2: Qualitative validation of the proposed multispectral fusion across key wind turbine components

Conclusion & Future Work

Key Achievements

0.93	0.90
mAP@.5	F1-Score

- Novel **ensemble-based deep learning** approach for wind turbine inspection
- Integration of YOLOv8 with specialized thermal model
- Enhanced detection of defects **missed in RGB-only** inspections

Limitations

- Computational overhead for real-time processing
- Precise sensor alignment requirements
- Environmental sensitivity in thermal data

Future Research Directions

- Optimizing ensemble for **real-time edge deployment**
- Advanced data fusion techniques to mitigate noise
- Incorporating **hyperspectral imaging** for enhanced defect detection
- Developing robust sensor calibration methods
- Expanding defect classes and training datasets