YOLO ENSEMBLE FOR UAV-BASED MULTISPECTRAL DEFECT DETECTION

in Wind Turbine Components

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

Khmelnytskyi National University, Ukraine
West Ukrainian National University, Ukraine
Casimir Pulaski Radom University, Poland

The 13th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems:
Technology and Applications • September 4-6, 2025 • Gliwice, Poland

Key Contributions

- **Multispectral** image fusion technique
- **Novel ensemble** learning approach
- **Superior** detection performance
- **mAP@.5: 0.93** • **F1-score: 0.90**

Abstract & Introduction

Research Problem

Wind Turbine Maintenance

- **Timely maintenance** critical for efficiency
- **Minor defects** pose economic & safety risks
- **UAV inspection** introduces complex challenges

Proposed Solution

YOLO Ensemble System

- **YOLO-based models** integrating visible & thermal
- **Bounding box fusion** to combine predictions
- **Enhanced detection** of visual & thermal defects

Key Findings

→ **Superior performance** over standalone YOLOv8

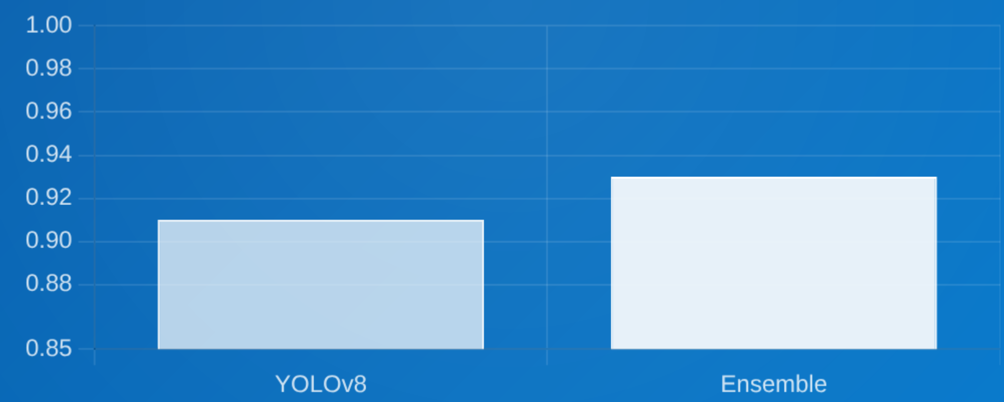
→ **Reliable solution** for diverse defect types

→ **Improved detection** in challenging conditions

Performance Metrics

mAP@.5: 0.93 ↑ 2.2% improvement

F1-score: 0.90 ↑ 2.3% improvement



3	**2**	**1**
DEFECT CLASSES	IMAGING CHANNELS	ENSEMBLE MODEL

Problem Statement & Motivation

Wind Turbine Challenges

Critical Role in Energy

- **Renewable energy transition** cornerstone
- **Efficiency depends** on maintenance
- **Undetected defects** = economic & safety risks

Types of Defects

- Cracks
- Corrosion
- Temperature Anomalies

Inspection Challenges

Physical Obstacles

- **Large-scale** & remote installations
- **Complex geometries** hard to inspect manually
- **Environmental conditions**: wind, glare, shadows

Technical Limitations

- **RGB-only imaging** misses thermal defects
- **Manual inspection** time-consuming & dangerous
- **Single-model approaches** lack robustness

30% of wind turbine failures caused by undetected component defects

Related Works

Evolution of UAV Monitoring

- RGB Sensors
- Thermal IR
- Multispectral

Data Processing Solutions

- **5G networks** for high-speed data transfer
- **Edge computing** for reduced latency
- **Advanced fusion techniques** from averaging to CNNs

Ensemble Techniques

- Balance **speed and accuracy**
- Combine **fast detectors** (YOLO) with **precise models** (Cascade R-CNN)
- **RGB-IR fusion** reduces missed defects in challenging conditions

Detection Algorithm Evolution

Approach	Advantages	Limitations
Hand-crafted features	Simple implementation	Limited accuracy
YOLO	Real-time speed	Lower precision
Faster R-CNN	Better accuracy	Slower inference
Cascade R-CNN	High precision	Computational cost

Research Gap

- Existing studies focus on **single detection models**
- Limited exploration of **ensemble learning** for multispectral data
- Need for **integrated approach** combining speed and accuracy

Our Contribution

- **Novel ensemble system** based on YOLO architectures
- Specialized training for **cracks, corrosion, overheating**
- Combining **visible and thermal imagery** for enhanced performance

Proposed Method - Overview

Overall Workflow

1. **Data Acquisition**
   UAV with RGB and thermal cameras

2. **Multispectral Fusion**
   Alignment and fusion of RGB and IR data

3. **Parallel Training**
   Baseline YOLOv8 and specialized thermal model

4. **Ensemble Fusion**
   Bounding box fusion algorithm

Major Contributions

Multispectral Fusion

- Fuses **RGB and thermal IR** data
- Creates **enriched image** representations
- Enhances visibility of **diverse defect types**

Ensemble Learning

- Combines **YOLOv8** with thermal model
- Utilizes **sophisticated bounding box fusion**
- Improves **detection accuracy** and robustness

Experimental Evaluation

- **Comprehensive testing** on multispectral data
- Comparison with **state-of-the-art** detectors
- Demonstrates **superior performance** metrics

Proposed Method - Data Collection & Fusion

Imaging Channels

RGB Channel

High-resolution optical images (4K/6K) for detecting **visual defects** like cracks and corrosion

IR Channel

Thermal images for detecting **temperature anomalies** indicating friction, electrical faults

Multispectral Fusion

Fusion Equation

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

Where g and h represent geometric transformations

Simple

Weighted sum for rapid processing

Advanced

Deep learning models (IFCNN)

Alignment Technique

- **Homography-based registration** for precise pixel-wise alignment
- Accounts for **differences in focal lengths** and spatial offsets
- Enables accurate **multispectral data fusion**

Defect Classes

Cracks (C1)	Corrosion (C2)	Overheating (C3)

- **Cracks:** Structural fractures compromising integrity
- **Corrosion:** Oxidative degradation on metallic surfaces
- **Overheating:** Temperature anomalies via IR channel

3

Defect Classes

Cracks · Corrosion · Overheating

Proposed Method - Ensemble Algorithm

Model Outputs

Baseline YOLOv8 (O_y)

$$O_y = \{D_{y,i} = (c_{y,i}, b_{y,i}, p_{y,i})\}$$

Thermal Model (O_{Mt})

$$O_{Mt} = \{D_{Mt,j} = (c_{Mt,j}, b_{Mt,j}, p_{Mt,j})\}$$

Bounding Box Fusion

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

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

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

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

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

Weighting Factor

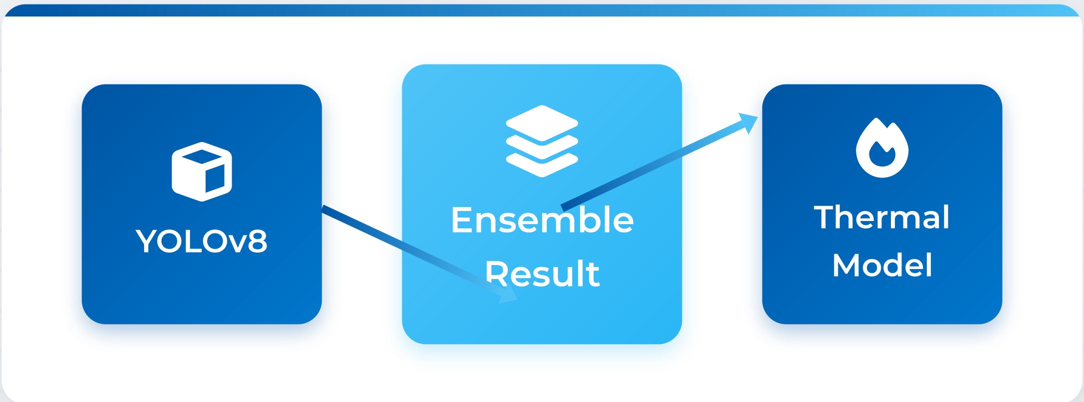
- $\gamma \in [0,1]$ controls model contribution
- $\gamma = 0.5$ assigns **equal importance**

Final Processing

- **Non-Maximum Suppression (NMS)** for final filtering
- Selects box with **highest confidence**
- Suppresses boxes with IoU above threshold (τ_{nms})

Algorithm 1: Key Steps

1. Initialize merged flags for all detections
2. Find overlapping detections of same class
3. Apply fusion equations to create new detection
4. Mark detections as merged
5. Add unmerged detections to combined list
6. Apply NMS to produce final detections



Experimental Setup

Dataset

Image Collection

- Base: **Blade30 dataset** with cracks and corrosion
- Augmentation: **670 additional images** with overheating

1,102
Base Images

670
Additional Images

Evaluation Metrics

- mAP@.5
- mAP@.5:.95
- Precision
- F1-Score

Training Details

Model Configuration

Optimizer:	**Adam**
Learning Rate:	**$\alpha = 0.001$**
Stopping:	**Early-stopping**
Specialized:	**Mt (IR-heavy)**

Comparison Models

Baseline & SOTA Models

- YOLOv8
- Faster R-CNN
- Cascade R-CNN
- EfficientDet

- All models trained on **same fused multispectral dataset**
- Specialized model Mt trained on **IR-heavy data**
- Comprehensive evaluation across **three defect classes**

Results - Performance Comparison

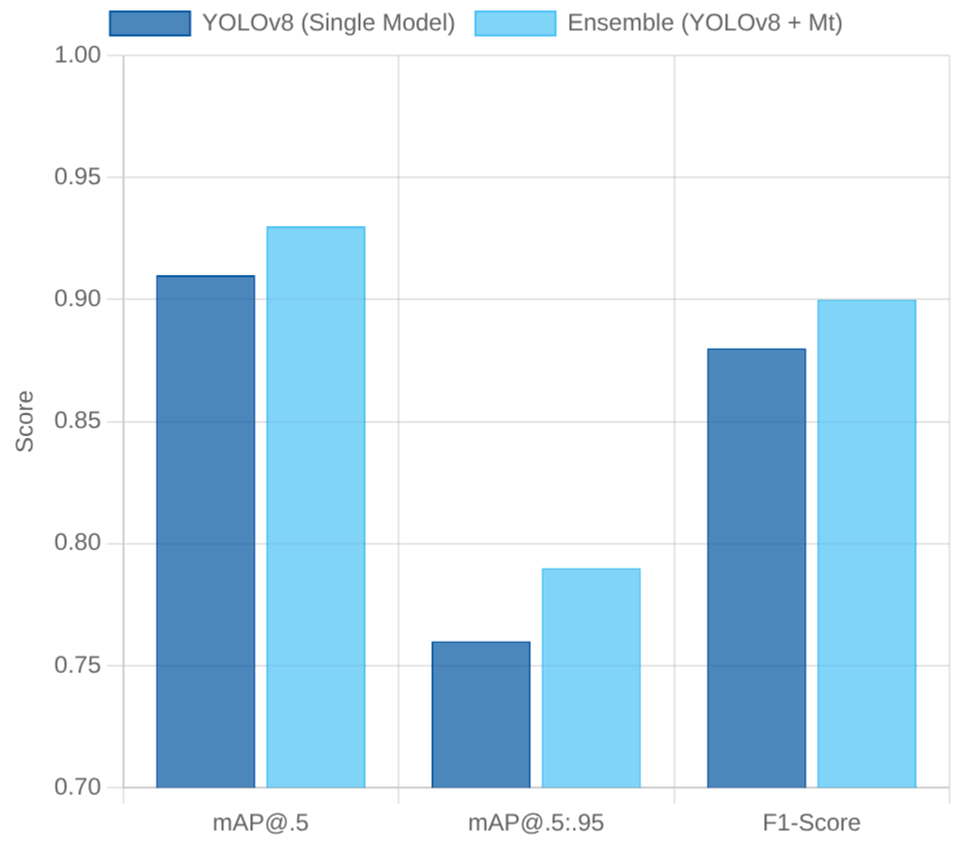
Comparative Performance

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**

Key Findings

- Ensemble achieved **2.2% improvement** in mAP@.5
- **3.9% gain** in stricter mAP@.5:.95 metric
- Mean F1-score increased from **0.88 to 0.90**

Performance Metrics Comparison



Cracks
+2.2%
F1-Score

Corrosion
+2.3%
F1-Score

Overheating
+3.5%
F1-Score

Results - Comparison with SOTA

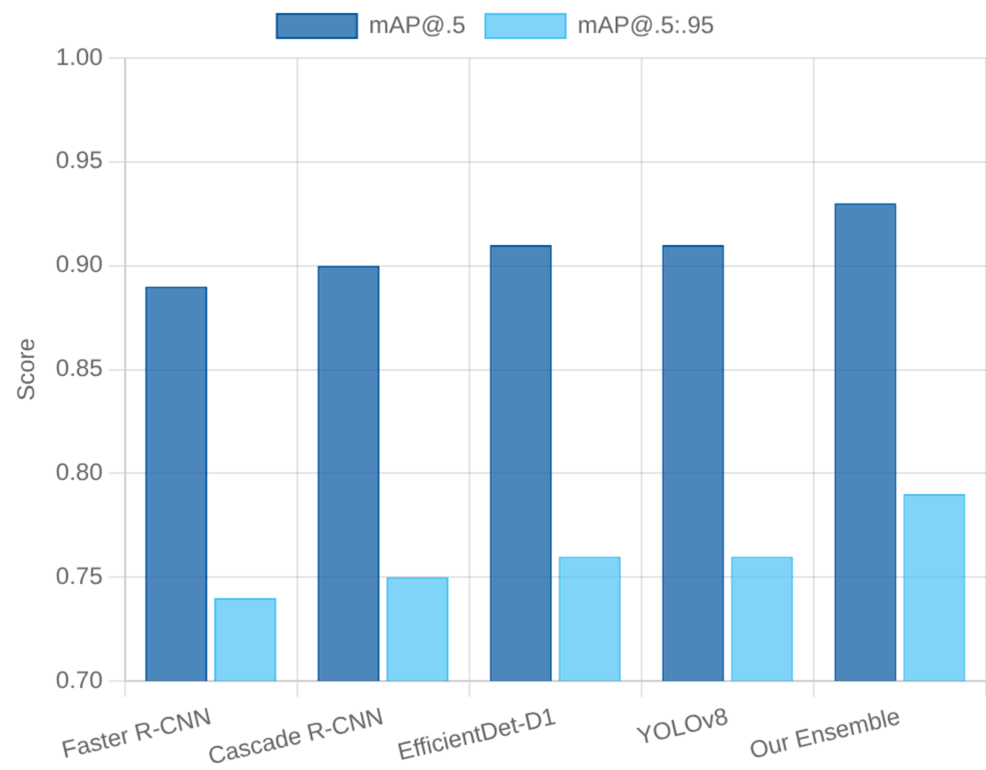
Comparative Performance

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	**0.93**	**0.79**

Key Findings

- Two-stage detectors show **good performance** but are outperformed by modern single-stage models
- Both EfficientDet-D1 and single YOLOv8 achieved **mAP@.5 of 0.91**
- Our ensemble achieved **highest scores** in both metrics
- **3.9% improvement** in stricter mAP@.5:.95 over baseline

Performance Across Models



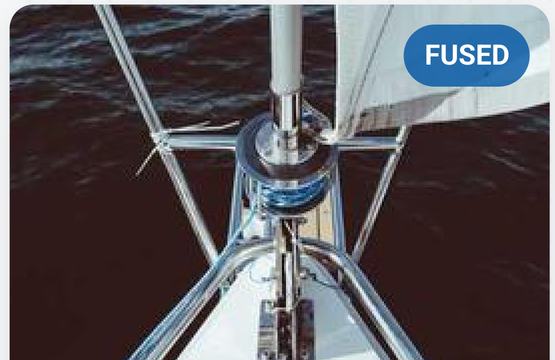
Why Our Ensemble Excels

- Capitalizes on **YOLOv8's feature extraction** power
- Leverages **specialized thermal model** for subtle defects
- **Bounding box fusion** combines complementary strengths
- Superior detection of **both visual and thermal defects**

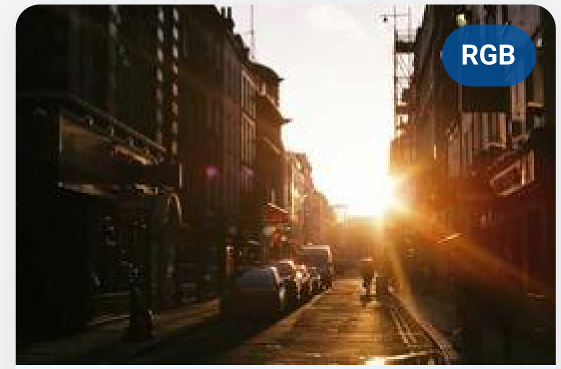
Results - Qualitative Analysis

Multispectral Fusion Benefits

Blade Crack



Blade Crack



Tower Corrosion

Tower Corrosion

Rotor Hub

Rotor Hub

Motor Component

Motor Component

Enhanced Visible Defects

- **Blade cracks** - Improved contrast along fracture lines
- **Tower corrosion** - Subtle degradation more distinct
- Fused images enable **tighter bounding boxes**
- Reduced impact of **shadows and surface texture**

Non-Visible Defect Detection

- **Rotor hub** - Reveals thermal patterns indicating stress
- **Motor component** - Exposes critical thermal hotspots
- Defects **completely missed** by RGB-only inspection
- Early detection of **potential failures**

Conclusions & Future Work

Key Contributions

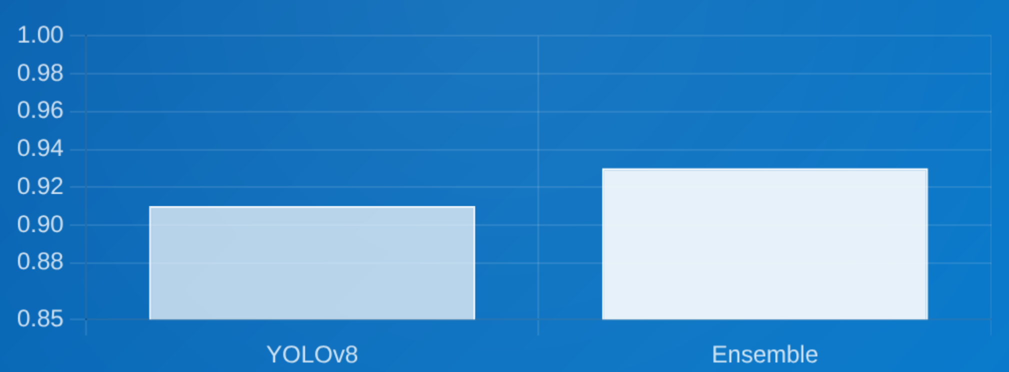
Major Achievements

- Novel **ensemble approach** combining YOLOv8 with thermal model
- Sophisticated **bounding box fusion algorithm** for multispectral data
- Comprehensive **multispectral dataset** with three defect classes

Performance Metrics

mAP@.5: 0.93 ↑ 2.2% improvement

F1-score: 0.90 ↑ 2.3% improvement



Limitations

- Increased **computational complexity** compared to single model
- Requires **precise alignment** of multispectral data

Future Research Directions

Research Opportunities

Optimization
Model compression & quantization for edge deployment

Additional Sensors
LiDAR & acoustic data integration

Advanced Fusion
Deep learning-based multispectral integration

Defect Classification
Severity assessment & predictive maintenance

Impact

Economic Benefits

Enhanced Safety

Scalable Solution