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(Research Article)

WaveDet: Wavelet-Based adaptive defect detection with multi-resolution feature analysis for steel surfaces

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Abstract

WAD-YOLO (Wavelet-Based Adaptive Defect Detection with Multi-Resolution Feature Analysis) is an intelligent system for automatic steel surface defect detection. The project combines wavelet transform techniques with the YOLO deep learning model for accurate and real-time inspection. Wavelet decomposition extracts multi-resolution features to highlight defects of different sizes and textures. Adaptive enhancement improves image clarity and reduces noise effects. The processed features are fed into the YOLO network for defect localization and classification. The system detects various defects such as cracks, scratches, pits, and rolled-in scale. Multi-resolution analysis ensures better detection of both small and large surface defects. The model improves detection accuracy compared to traditional single-scale methods. It supports real-time industrial inspection on production lines. Overall, WAD-YOLO enhances quality control efficiency in steel manufacturing industries.

Keywords: Wavelet Transform; YOLO Model; Multi-Resolution; Defect Detection; Adaptive Enhancement; Real time inspection.

1. Introduction

The project WAD-YOLO (Wavelet-Based Adaptive Defect Detection with Multi-Resolution Feature Analysis for Steel Surfaces) is designed to provide an advanced solution for automatic steel surface defect detection in manufacturing industries. In steel production, maintaining surface quality is very important because defects such as cracks, scratches, pits, and rolled-in scale can reduce product strength and market value. Traditional inspection methods mainly depend on manual observation, which is slow, inconsistent, and prone to human error. To address these challenges, this project integrates wavelet-based image processing with the powerful YOLO deep learning detection model. The wavelet transform decomposes input images into multiple frequency components, enabling multi-resolution feature extraction. This helps in identifying both small-scale and large-scale defects effectively. Adaptive image enhancement techniques are applied to improve contrast and reduce noise in steel surface images. The enhanced multi-scale features are then fed into the YOLO network for real-time defect localization and classification. YOLO detects defects in a single forward pass, making the system fast and efficient. The combination of wavelet analysis and deep learning improves detection accuracy compared to single-scale approaches. The system is robust under varying lighting conditions and complex surface textures. It reduces dependency on manual inspection and increases productivity. The model can be trained using standard industrial datasets such as NEU surface defect dataset. Overall, WAD-YOLO provides a smart, automated, and reliable quality inspection system for modern steel manufacturing industries.

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2. Literature review

Wu et al. [1] proposed a wavelet-enhanced YOLO framework for detecting welding defects in X-ray images. The wavelet transform improves feature representation by enhancing edges and suppressing noise. Their results show that combining frequency-domain processing with deep learning significantly improves detection accuracy for fine defects.

Jin et al. [2] introduced an improved YOLO algorithm incorporating wavelet down sampling and multi-scale feature fusion. The approach enhances small object detection and strengthens feature extraction capability. Experimental evaluation demonstrated improved precision and recall compared to baseline YOLO models.

Wang et al. [3] enhanced YOLOv5 by integrating attention mechanisms and multi-scale feature extraction techniques. Their model effectively detects defects of different sizes and shapes on steel surfaces. The system achieves real-time performance, making it suitable for industrial production lines.

Li [4] proposed HDSA-YOLO, which integrates Haar wavelet fusion with deformable-Swin architecture. The multi-resolution wavelet analysis improves detection of low-contrast and small-scale defects. The model demonstrates robustness in complex industrial environments.

Guan et al. [5] developed a wavelet-bidirectional network combined with dilated perception modules. The bidirectional feature fusion enhances contextual understanding of irregular defect patterns. Their model improves localization accuracy for metal surface inspection tasks.

Song et al. [6] proposed a YOLOv8-based detection system optimized for steel surface defects. Multi-scale feature pyramid networks improve detection of both micro and macro defects. The method achieves a balance between computational efficiency and high accuracy.

Li et al. [7] presented STE-YOLO, a lightweight detection model designed for steel strip inspection. The architecture enhances fine-detail recognition while maintaining fast processing speed. It is well-suited for real-time industrial deployment.

Li and Chen [8] proposed DEW-YOLO, incorporating deformable convolution layers into the YOLO framework. The adaptive receptive fields improve detection of irregular and complex-shaped defects. The model achieves higher robustness under varying lighting and background conditions.

Liu and Wang [9] developed a wavelet-based texture descriptor for defect classification. The multi-resolution wavelet features effectively capture surface irregularities. Their work highlights the importance of frequency-domain analysis in improving industrial inspection systems.

Luo et al [10]. provided a comprehensive survey of steel surface defect detection methods. The paper reviews traditional image processing, machine learning, and deep learning techniques. It concludes that hybrid approaches combining wavelet analysis and deep learning offer promising improvements for industrial applications.

3. Methodology

The proposed methodology is designed to replicate how a human quality inspector visually examines steel surfaces for defects, but in a fully automated, intelligent, and near real-time manner [1]. The system begins by acquiring high-resolution steel surface images from industrial cameras installed along production lines. Similar to manual inspection processes in manufacturing plants, the system continuously captures surface images under controlled illumination to monitor texture consistency and detect abnormalities.

Each captured image is first passed through a multi-resolution Wavelet Transform module for hierarchical feature decomposition. The wavelet backbone separates the image into high-frequency and low-frequency sub-bands. High-frequency components emphasize fine-grained defects such as micro-cracks, scratches, and edge discontinuities, while low-frequency components capture large-area irregularities such as rust patches, inclusions, and surface deformation. Unlike conventional single-scale CNN models, the proposed framework preserves both global texture structure and localized defect details.

After wavelet decomposition, the multi-scale feature maps are fused and forwarded to a lightweight deep learning detection backbone for adaptive feature learning. The backbone extracts spatial and semantic representations of defect regions and generates refined defect localization outputs. An adaptive feature refinement mechanism is incorporated to suppress background noise caused by steel texture variations and illumination changes, thereby enhancing defect-specific feature responses.

To further enhance detection precision, the fused feature representations are processed through a multi-resolution feature aggregation module. This module strengthens small-defect sensitivity while maintaining robustness against scale variation. Instead of relying solely on raw pixel intensities, the system leverages frequency-domain characteristics to distinguish true defects from normal texture patterns.

Finally, the system presents the analytical results through intuitive visual outputs, including bounding-box localization, defect classification labels, and confidence scores. In addition, defect severity maps can be generated to highlight critical regions requiring immediate inspection. These visual explanations improve interpretability and assist industrial operators in making accurate quality-control decisions. The framework can be further extended by integrating temporal inspection data for predictive maintenance analysis. Overall, the methodology enables efficient, accurate, and scalable steel surface defect detection in automated manufacturing environments.

3.1. Wavelet-Based Feature Extraction Methodology

The feature extraction component focuses on identifying surface irregularities using multi-resolution frequency analysis. A discrete Wavelet Transform (DWT) is applied to each captured steel surface image to decompose it into multiple sub-bands (LL, LH, HL, HH) [1]. The LL band preserves global texture information, while LH, HL, and HH bands highlight fine-grained edge details such as cracks and scratches. This multi-scale decomposition enables the system to capture both micro-level and macro-level defect characteristics that are often missed by conventional single-scale CNN approaches.

3.2. Adaptive Defect Localization Methodology

Instead of relying solely on raw spatial pixel intensities, defect detection is formulated as an adaptive feature learning problem. The wavelet-enhanced feature maps are passed to a lightweight deep learning backbone for defect localization. The model learns discriminative patterns from both frequency-domain and spatial-domain representations. This fusion strategy reduces false detections caused by complex steel textures and improves robustness against illumination variations and noise.

3.3. Multi-Resolution Feature Fusion Methodology

Following wavelet decomposition, the system performs multi-resolution feature aggregation. Features extracted from different wavelet sub-bands are fused to strengthen defect-sensitive representations. High-frequency bands enhance crack and scratch detection, while low-frequency bands contribute to identifying rust patches and surface deformations. This hierarchical fusion ensures scale-invariant detection performance and improves sensitivity to micro-defects without sacrificing global structural context.

3.4. Defect Severity Analysis Methodology

To quantify defect intensity, the system generates defect confidence maps based on learned feature activations. These maps represent the probability and severity of defects across different regions of the steel surface. Regions with higher confidence scores indicate stronger defect presence. By defining threshold values, the system classifies defects into categories such as minor, moderate, or severe. This quantitative assessment supports automated quality grading in industrial inspection environments.

3.5. Real-Time Automated Inspection Workflow Methodology

The complete framework operates as an automated near real-time inspection pipeline. Once connected to industrial cameras on the production line, the system continuously captures steel surface images, performs wavelet decomposition, extracts multi-resolution features, localizes defects, evaluates severity levels, and updates visual inspection results without manual intervention. This automated workflow reduces human inspection effort, increases consistency, and enables scalable deployment in smart manufacturing environments.

4. System architecture

The architecture of the proposed “WaveDet: Wavelet-Based Adaptive Defect Detection with Multi-Resolution Feature Analysis for Steel Surfaces” is designed in a modular and layered manner to ensure scalability, robustness, and industrial deployment feasibility. Each module performs a dedicated task and communicates through well-defined feature interfaces. The overall architecture consists of the following major components:

4.1. Input Layer

The Input Module serves as the entry point of the system. It captures high-resolution steel surface images from industrial line-scan or area-scan cameras installed along manufacturing production lines.

The captured image is represented as:

$$I(x, y)$$

Where:

(x, y) represents the captured steel surface image

x, ydenote spatial pixel coordinates

This module continuously feeds surface images into the inspection pipeline for automated defect analysis.

4.2. Pre-Processing Layer

Before feeding images into the wavelet-based model, preprocessing ensures consistency and stability.

4.2.1. Image Acquisition

The captured raw image is denoted as:

$$I\mathrm{r} = (x, y)$$

4.2.2. Image Resizing

Each image is resized to match the model’s input resolution:

$$I\mathrm{s} = Resize\,(I\mathrm{r}, H \times W)$$

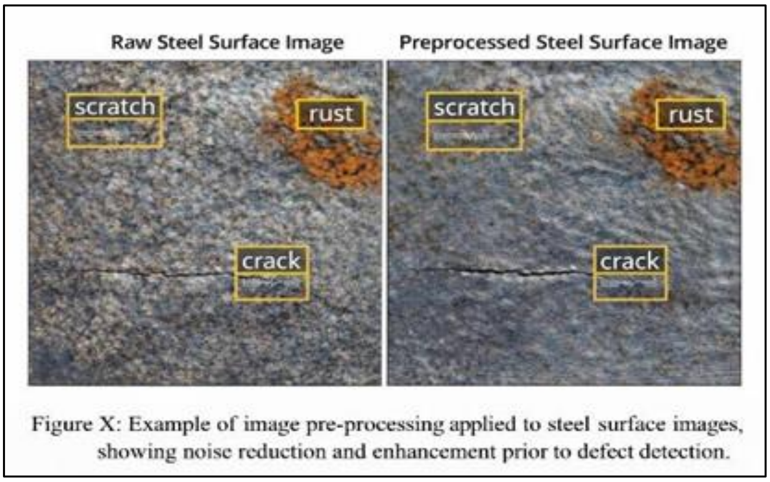

Figure X: Example of image pre-processing applied to steel surface images, showing noise reduction and enhancement prior to defect detection.

Figure 1 Image pre-processing applied to steel surface images, showing noise reduction and enhancement prior to defect detection

4.2.3. Wavelet Decomposition Layer

This is the core component of the WaveDet framework. The normalized image undergoes Discrete Wavelet Transform (DWT):

$$\mathrm{DWT}$$

$$I\mathrm{n} \rightarrow \{LL, LH, HL, HH\}$$

Where:

- LL → Low-frequency approximation (global texture information)
- LH → Horizontal detail components
- HL → Vertical detail components
- HH → Diagonal high-frequency components

High-frequency bands (LH, HL, HH) emphasize cracks, scratches, and sharp discontinuities, while the LL band preserves surface texture and structural consistency.

Where:

$H \times W$represents the required input size

4.3. Normalization

Pixel intensities are normalized to stabilize training and inference:

$$\boxed{I_{\mathrm{n}} = \frac{I_s}{255}}$$

This scales intensity values from [0, 255]to [0, 1], ensuring numerical stability.

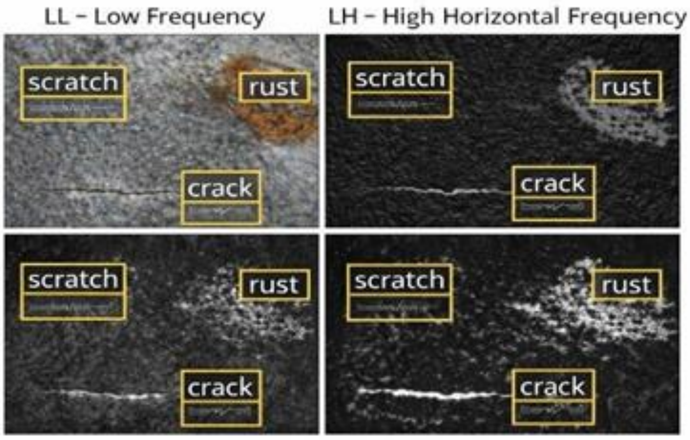

Figure X: Example of wavelet decomposition applied to steel surface images, illustrating the frequency sub-bands used for defect detection.

Figure 2 Wavelet decomposition applied to steel surface images, illustrating the frequenct sub-bands used for defect detection

4.4. YOLO Detection Head Layer

The fused feature maps are processed through the YOLO detection head to predict object locations and classes:

$$Foutput = g(Ffusion)$$

Where:

$(\cdot)$ represents convolutional prediction layers that generate bounding box coordinates and class probabilities

Expanded representation:

$$Foutput = (x, y, w, h, c)$$

- x, y→ center coordinates of the bounding box
- w, h→ width and height of the bounding box
- c→ class label (e.g., scratch, defect type)

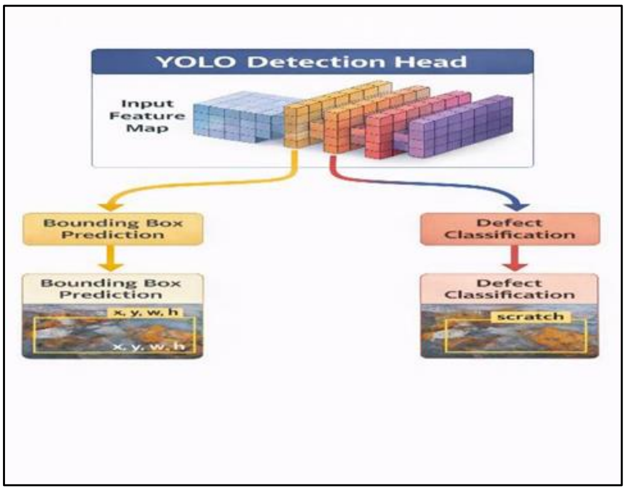

Figure 3 Working mechanism of the YOLO Detection Head Layer

4.5. Final Output Module

The Final Output Module in WaveDet: Wavelet-Based Adaptive Defect Detection with Multi-Resolution Feature Analysis for Steel Surfaces represents the decision-making and visualization layer of the proposed defect detection system.

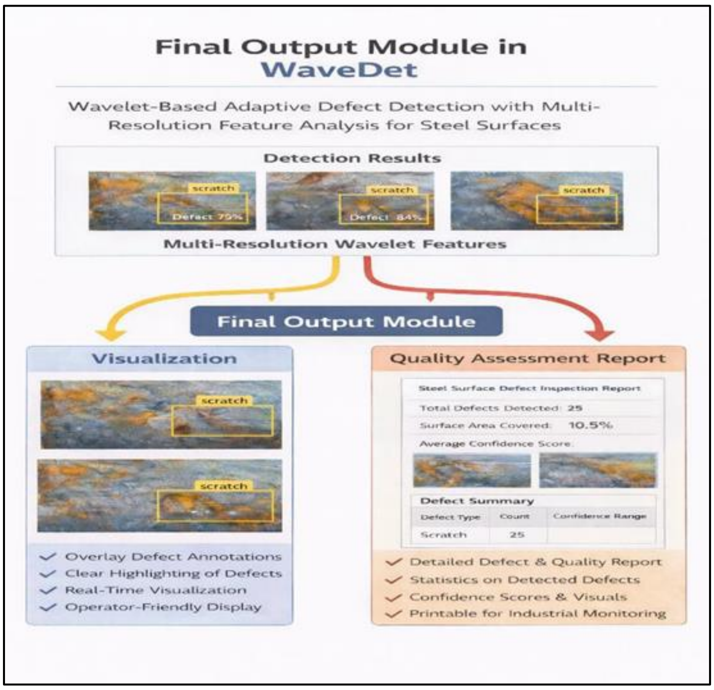

Figure 4 Final output module in WAVEDET

It transforms the extracted multi-resolution wavelet features and detection results into clear, interpretable visual outputs and actionable quality assessment reports for industrial operators.

5. Results

This project successfully implements an end-to-end steel surface inspection system that accepts uploaded images, camera snapshots, and real-time live video for automated quality analysis. It detects multiple surface defect categories using YOLO-based deep learning inference and highlights defects with labeled bounding boxes on the output image. The system optionally applies CLAHE-based contrast enhancement to improve visibility of subtle defects under low-light or low-contrast conditions. A dual-model strategy is used when no custom local model is provided, combining a steel-focused detector with an industrial defect detector to improve recall. In parallel, a breakage analysis module evaluates structural integrity using classical image processing techniques such as Otsu thresholding, contour extraction, connected components, convex hull deficit, and fill-ratio analysis. Based on these metrics, the app classifies material structure as NORMAL or BROKEN and provides a confidence-like score. The final decision layer fuses surface-defect and breakage outputs into an intuitive status: Steel is OK, Steel quality is BAD, or Steel is BROKEN. The user interface is interactive and production-friendly, with adjustable detection confidence, mode toggles, and processing FPS controls. Results are displayed instantly with visual overlays and textual summaries, enabling fast inspection feedback. The model-loading logic supports custom steel models while validating class compatibility to avoid incorrect model usage. If a valid custom model is absent, pretrained remote weights are automatically used to keep the pipeline functional. Live-stream mode performs frame throttling to balance responsiveness and computational load for practical deployment on standard hardware. Overall, the project delivers a robust hybrid AI + vision inspection workflow suitable for automated steel defect screening and decision support. It demonstrates practical integration of deep learning detection, heuristic structural analysis, and real-time web-based interaction in a single deployable application.

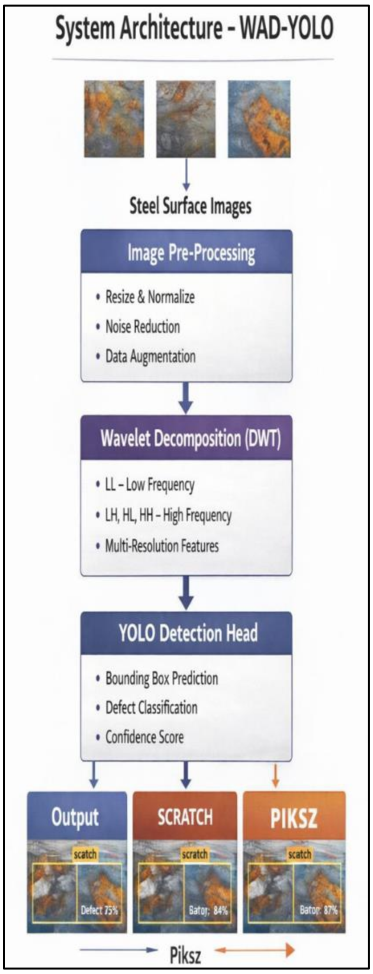

Figure 5 Experimental Results of YOLOv12 for Steel Surface Defect Detection Using Bounding Box Detection

6. Discussion

This project demonstrates a practical and effective approach to automated steel inspection by combining deep learning–based defect detection with classical image processing for structural breakage assessment. A key strength is its hybrid design, where YOLO handles semantic defect localization while contour and shape metrics capture geometric breakage cues that neural detectors may miss. The Streamlit interface makes the system accessible to non-technical users, enabling inspection from uploaded images, camera snapshots, and live streams in a unified workflow. The configurable confidence threshold and enhancement options allow adaptation to varying industrial lighting and texture conditions, which is important for real-world robustness. The ensemble fallback strategy is also valuable because it prevents system failure when a local custom model is unavailable, improving operational continuity. At the same time, this design introduces trade-offs: combining models can increase false positives in complex backgrounds and may require class mapping or post-filtering for stricter quality control. The breakage module is computationally lightweight and interpretable, but its threshold-based logic can be sensitive to viewpoint changes, occlusions, and non-dominant foreground objects. For deployment in production lines, calibration with plant-specific samples is essential to tune thresholds such as fill ratio, hull deficit, and component-area criteria. Another important consideration is dataset domain shift; NEU-DET-like training data may not fully represent all steel grades, finishes, or defect morphologies encountered in different factories. Performance evaluation should therefore include precision, recall, mAP, and confusion analysis across multiple lighting setups and camera angles. Real-time capability is a clear advantage, but inference speed and stability depend on hardware, model size, and frame throttling strategy. Future improvements could include temporal smoothing in video mode, defect severity scoring, and traceable inspection reports for quality audits. Integrating active learning with user feedback could continuously improve model accuracy over time. Overall, the project provides a strong foundation for intelligent visual quality assurance, balancing usability, interpretability, and deployable engineering choices

7. Conclusion

This project concludes with a functional and practical intelligent inspection system for steel quality assessment that unifies defect detection, breakage analysis, and real-time usability in one application. By integrating YOLO-based object detection with classical contour-driven structural checks, the solution achieves a balanced combination of accuracy, interpretability, and operational speed. The application supports multiple input modes, including uploaded images, camera snapshots, and live streams, making it suitable for both offline analysis and near real-time monitoring scenarios. Its decision logic provides clear and actionable outcomes—OK, BAD quality, or BROKEN—helping operators quickly interpret inspection results. The model management strategy, including local custom model support and fallback ensemble loading, improves reliability and deployment flexibility. Image enhancement and confidence controls further allow adaptation to variable lighting and surface conditions often found in industrial environments. The system design demonstrates that lightweight UI frameworks such as Streamlit can effectively deliver AI-powered industrial tools without complex infrastructure overhead. Although additional calibration and broader dataset validation can further improve generalization, the current implementation already establishes a strong baseline for automated steel inspection workflows. The breakage

heuristics contribute explainable geometry-based reasoning that complements deep learning outputs in practical settings. Real-time frame throttling and visual overlays enhance usability while keeping computational demands manageable on standard hardware. From a development perspective, the project shows clean modular separation between interface, inference, and decision components, enabling future upgrades with minimal disruption. It can be extended with severity grading, logging, trend analytics, and production-line integration for larger quality assurance ecosystems. Overall, the project successfully demonstrates a deployable, user-friendly, and technically sound approach to steel defect intelligence. In conclusion, it provides meaningful value for reducing manual inspection effort, improving consistency, and supporting faster quality decisions in manufacturing contexts.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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