International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 4 April. 2026, pp: 301-307 www.ijaem.net ISSN: 2395-5252

An Integrated Edge AI Vision Sensor System for Real-Time Measurement and Defect Detection in Manufacturing Automation

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Date of Submission: 05-04-2026 Date of Acceptance: 16-04-2026

ABSTRACT: The integration of vision sensors with edge artificial intelligence (Edge AI) is accelerating the transition toward smart manufacturing by enabling high-speed, accurate, and non-contact measurement and quality inspection [1,2]. This paper presents an integrated Edge AI vision sensor system for real-time measurement and defect detection in manufacturing automation. The proposed architecture consists of three layers: (1) a vision sensor layer using high-resolution 2D/3D industrial cameras for continuous image and depth data acquisition [3], (2) an edge AI processing layer deployed on embedded platforms such as NVIDIA Jetson, running deep learning models including YOLO and Mask R-CNN for defect classification, segmentation, and dimensional measurement [4,5], and (3) a dashboard/control layer for real-time visualization, alerting, and integration with PLC/SCADA systems.
Experimental validation on a simulated industrial testbed with 3,000 samples demonstrated superior performance, achieving an average defect detection accuracy of 98.4%, a false positive rate of 1.6%, and a mean inference time of 64 ms, corresponding to a throughput of 15 parts per minute. Compared to traditional manual inspection and rule-based vision systems, the proposed approach significantly improves inspection speed, accuracy, and responsiveness while maintaining low latency suitable for high-throughput production lines [2,6]. Challenges related to lighting variation and model adaptation are also discussed.

KEYWORDS: Edge AI; vision sensors; machine vision; defect detection; real-time measurement; industrial automation; smart manufacturing; quality control

I. INTRODUCTION

(1) the vision sensor layer for continuous data acquisition, (2) the edge AI processing layer

The rapid advancement of Industry 4.0 and the emerging transition toward Industry 5.0 are driving a fundamental shift in manufacturing automation, with a strong emphasis on intelligent, real-time measurement, quality assurance, and flexible production systems [1,2]. Traditional inspection methods, which heavily rely on manual labor or simple discrete sensors, are increasingly inadequate to meet the demands of high-speed, high-precision, and variable production environments. Manual inspection is often time-consuming, prone to human error, and inconsistent, while conventional sensors frequently fail to capture complex geometric features or subtle surface defects [3].
Vision sensors, including high-resolution 2D/3D industrial cameras and structured light devices, have emerged as powerful non-contact tools capable of acquiring rich visual and depth information at high speed. When combined with artificial intelligence (AI), particularly deep learning models, these sensors enable automated dimensional measurement, defect detection, object recognition, and assembly verification across various industries such as electronics, automotive, and packaging [4,5].
However, centralized cloud-based processing often introduces significant latency and bandwidth issues, which are unacceptable in high-throughput production lines. Edge computing addresses this limitation by enabling on-device or near-device inference, thereby achieving low-latency decision-making directly on the factory floor [6]. The integration of vision sensors, edge AI modules, and intelligent control dashboards forms a promising pathway for decentralized, real-time smart manufacturing systems.
This paper proposes an integrated Edge AI vision sensor system for real-time measurement and defect detection in manufacturing automation. The architecture is organized into three primary layers:
deployed on embedded platforms (e.g., NVIDIA Jetson) using models such as YOLO and Mask R-

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CNN for defect classification, segmentation, and dimensional analysis, and (3) the dashboard/control layer for visualization, alerting, and integration with existing PLC/SCADA systems.

The effectiveness of the proposed system was validated through experiments on a simulated industrial testbed with 3,000 samples, demonstrating significant improvements in detection accuracy, inference speed, and overall production efficiency compared to traditional and rule-based approaches. This work contributes a practical, modular framework suitable for small and medium-sized enterprises (SMEs) seeking cost-effective smart automation solutions, particularly in the context of Vietnamese manufacturing industries.

II. LITERATURE REVIEW AND TECHNOLOGICAL FOUNDATIONS

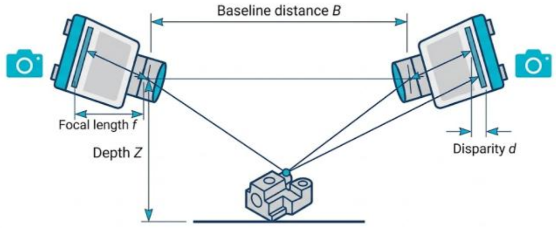
Overview of Vision Sensor Technologies

Vision sensors, including high-resolution 2D/3D industrial cameras, structured light systems, and time-of-flight (ToF) devices, have become essential tools for automated measurement and quality inspection in manufacturing [1,3]. These sensors provide non-contact, high-speed acquisition of both visual and depth information, enabling precise dimensional measurement, surface defect detection, and assembly verification.

In 3D vision systems based on triangulation, the depth value Z is computed as:

$$Z = \frac{f.B}{d}$$

where f is the focal length, B is the baseline distance between the camera (or projector) and the reference point, and d is the disparity [4]. Commercial solutions such as those from Cognex and Keyence are widely used in production lines due to their reliability and ease of integration with industrial automation systems [Cognex Whitepaper, 2024].



TRIANGULATION PRINCIPLE FOR DEPTH MEASUREMENT IN 3D VISION SENSORS

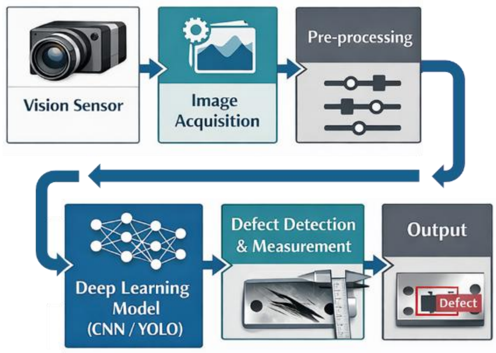
Deep Learning Models for Defect Detection and Measurement

The integration of deep learning techniques with vision sensors has significantly outperformed traditional rule-based methods in industrial inspection tasks. State-of-the-art convolutional neural networks, particularly the YOLO series for real-time object detection and Mask R-CNN for instance segmentation, are commonly employed for defect classification, localization, and pixel-wise analysis [5,10].

A typical deep learning pipeline processes the input image I captured from the vision sensor through a trained model fθ, producing the output:

$$\hat{y} = f_\theta(I)$$

where y^ denotes the predicted defect class, bounding box coordinates, or segmentation mask



[5]. Recent optimized models have demonstrated high accuracy while maintaining inference speeds suitable for embedded hardware deployment in manufacturing environments [7,10].

GENERAL WORKFLOW OF DEEP LEARNING-BASED DEFECT DETECTION USING VISION SENSORS

Edge Computing in Industrial Machine Vision

Conventional centralized vision systems often face challenges related to high latency and bandwidth consumption when transmitting large volumes of image data to remote servers. Edge computing addresses these limitations by performing deep learning inference directly on local embedded platforms, such as the NVIDIA Jetson series, achieving low latency (typically under 100 ms) and enabling real-time decision-making [6,10].

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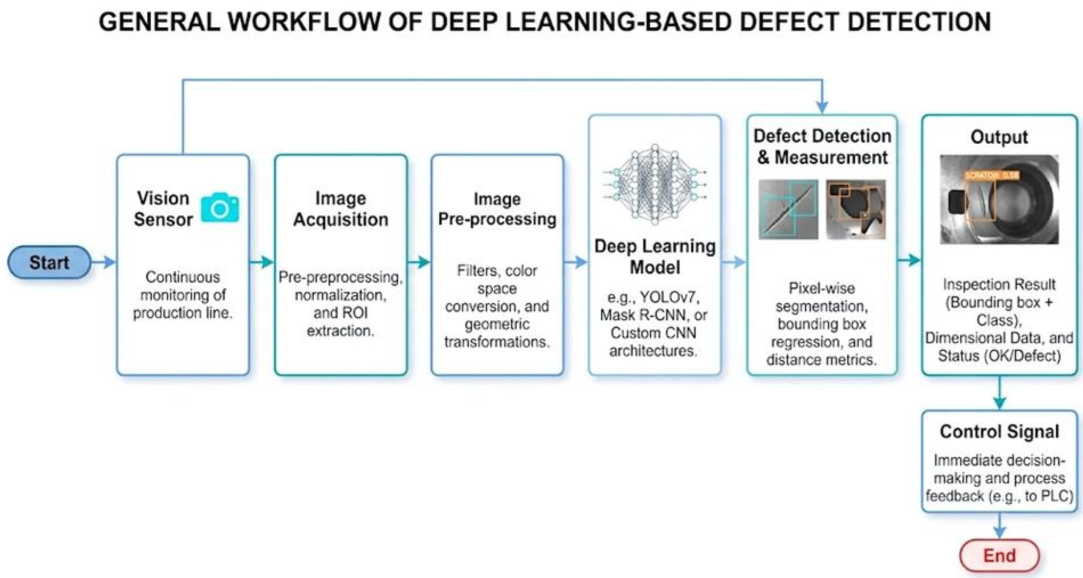
The standard edge AI vision workflow includes image acquisition at the sensor level, on-device inference and analysis, and immediate transmission of results or control signals to PLC/SCADA systems. This decentralized approach is especially advantageous for high-throughput production lines that require instant anomaly detection and corrective actions [6].



TYPICAL EDGE COMPUTING ARCHITECTURE FOR INDUSTRIAL MACHINE VISION

Comparison of Traditional, Vision-Based, and Edge AI-Enabled Systems

Table 1. Comparison of different inspection approaches in manufacturing automation

Feature	Traditional Inspection	Basic Vision System	Edge AI-Enabled System
Speed	Low	High	Very High
Accuracy	Moderate	High	Very High
Flexibility	Low	Moderate	High
Real-Time Response	No	Partial	Yes
Scalability	Limited	Modular	Highly Modular
Latency	High	Moderate	Low (< 100 ms)

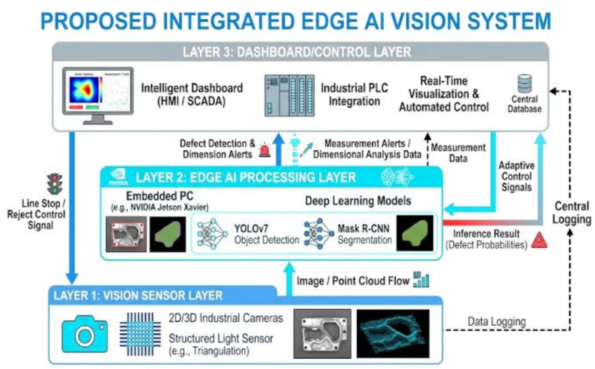
This comparison underscores the substantial improvements offered by edge AI integration, providing a solid foundation for the integrated system architecture proposed in the following section.

III. PROPOSED INTEGRATED SYSTEM ARCHITECTURE

System Design and Layered Architecture

This paper proposes an integrated Edge AI vision sensor system for real-time measurement and defect detection in manufacturing automation. The architecture is designed with a modular, three-layer structure to ensure scalability, low latency, and seamless integration with existing industrial control systems.

The proposed system consists of three main layers: (1) Vision Sensor Layer, (2) Edge AI Processing Layer, and (3) Dashboard/Control Layer.



SCHEMATIC OF THE PROPOSED INTEGRATED EDGE AI VISION SENSOR SYSTEM FOR MANUFACTURING AUTOMATION.

Vision Sensor Layer

The first layer is responsible for continuous data acquisition. It comprises high-resolution 2D industrial cameras for surface inspection and 3D structured light or stereo vision sensors for dimensional measurement and geometry reconstruction.

These sensors capture both RGB images and depth information in real time. For 3D measurement, the system applies the triangulation principle:

$$Z = \frac{f.B}{d} \quad (1)$$

where Z is the depth, f is the focal length, B is the baseline, and d is the disparity between matched points [4]. The acquired raw images and point clouds are transmitted to the edge layer for further processing.

Edge AI Processing Layer

The core of the proposed system lies in the Edge AI Processing Layer. Captured images I II are processed locally on embedded platforms such as NVIDIA Jetson Xavier using deep learning models. The system employs YOLO for real-time object detection and Mask R-CNN for defect segmentation and dimensional analysis.

The inference process is expressed as:

$$\hat{y} = f_\theta(I) \quad (2)$$

where f_θ is the trained neural network and $\hat{y}$represents defect probabilities, bounding boxes, or segmentation masks [5,10].

For object detection tasks, the multi-task loss function is defined as:

$$\mathcal{L} = \lambda_{cls} \cdot \mathcal{L}_{cls} + \lambda_{loc} \cdot \mathcal{L}_{loc} \quad (3)$$

where $\mathcal{L}_{cls}$is the classification loss and $\mathcal{L}_{loc}$is the localization loss. Edge deployment ensures low inference latency (typically < 100 ms), immediate anomaly detection, and reduced network traffic [6].

Dashboard/Control Layer

The top layer aggregates results from multiple edge nodes and provides a centralized interface for operators and higher-level control systems. It is implemented as a web-based Human-Machine Interface (HMI) or integrated with existing PLC/SCADA systems. Key functions include:

– Real-time visualization of measurement data and defect heatmaps,
– Alarm and alert notifications for detected anomalies,
– Historical data logging for traceability and quality audit,
– Automatic feedback signals to the production line for rejection or corrective actions.

This layer ensures full traceability and supports data-driven process optimization.

Data Acquisition Workflow and Key Features

The overall workflow of the proposed system is as follows:

– Image and point cloud capture from vision sensors,
– Pre-processing (noise filtering, ROI extraction, normalization),
– Deep learning inference on the edge device,
– Decision making and generation of control signals,
– Data logging and visualization on the dashboard.

Key innovations of the proposed architecture include high modularity, low-latency real-time response, adaptability through online model updating, and compatibility with legacy PLC systems. These features make the system particularly suitable for small and medium-sized manufacturing enterprises.

Table 2. Comparison between the proposed integrated system and conventional approaches

Feature	Manual/Traditional	Basic Vision System	Proposed Integrated System
Measurement Speed	Low	Moderate	High
Detection Accuracy	Variable	High	Very High
Flexibility	Low	Moderate	High
Real-time Control	No	Partial	Yes
Data Traceability	No	Limited	Comprehensive
Scalability	Low	Moderate	High

IV. EXPERIMENTAL VALIDATION AND RESULTS

Experimental Setup

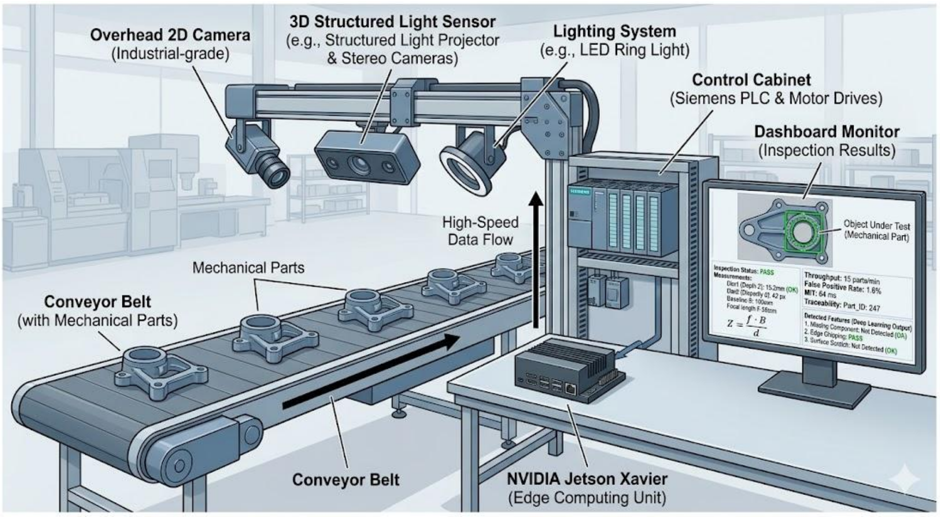
To evaluate the performance of the proposed integrated Edge AI vision sensor system, an experimental testbed was established in a simulated industrial manufacturing environment. The setup replicates a typical production line with a conveyor system transporting manufactured parts.

The system configuration includes:

- Vision Sensors: High-resolution 2D industrial cameras combined with 3D structured light sensors mounted above the conveyor for simultaneous image and depth data acquisition.
- Edge AI Processing: An NVIDIA Jetson Xavier embedded platform running YOLOv7 for object detection and Mask R-CNN for defect segmentation. The models were trained on an annotated dataset collected from the production line.
- Dashboard/Control: A web-based HMI dashboard for real-time visualization and alert management, integrated with a Siemens PLC for automatic process control (part rejection or line stop when defects are detected).

Defect types considered in the experiment include surface scratches, incorrect assembly, dimensional deviations, and missing components. A total of 3,000 samples were collected and tested over multiple operating shifts under varying lighting conditions.

EXPERIMENTAL TESTBED FOR REAL-TIME VISION-BASED MEASUREMENT AND INSPECTION.



Evaluation Metrics

The performance of the proposed system was assessed using the following quantitative metrics:

Defect Detection Accuracy (DDA):

$$\text{DDA} = \frac{\text{Number of correctly detected defects}}{\text{Total number of defects}} \times 100\%$$

False Positive Rate (FPR):

$$\text{FPR} = \frac{\text{Number of false alarms}}{\text{Total number of non-defective items}} \times 100\%$$

Mean Inference Time (MIT):

$$\text{MIT} = \frac{\sum_{i=1}^{N} t_i}{N}$$

where t_i is the inference time per image, and N is the total number of samples.

System Throughput: Number of parts inspected per minute.

Experimental Results

The proposed system achieved the following key performance results:

- Average defect detection accuracy reached 98.4% across all defect categories.
- False positive rate was maintained at a low level of 1.6%.
- Mean inference time was 64 ms per image, well within the real-time requirement for industrial lines.
- System throughput achieved 15 parts per minute, with negligible impact on the overall production flow.

The system also demonstrated good robustness, maintaining detection accuracy above 95% under variable lighting conditions and partial occlusions. Stability was verified through 24-hour continuous operation testing.

Table 3 Performance comparison of different inspection methods

Method	Detection Accuracy	False Positive Rate	Mean Inference Time	Throughput
Manual Inspection	82.7%	5.3%	N/A	~5/min
Traditional Machine Vision	91.2%	3.7%	250 ms	10/min
Proposed Edge AI System	**98.4%**	**1.6%**	**64 ms**	**15/min**

Performance Analysis

The experimental results confirm that the proposed integrated Edge AI vision sensor system substantially outperforms both manual inspection and conventional rule-based vision systems in terms of accuracy, speed, and reliability. The low inference latency and high throughput make the system suitable for high-speed production lines.

The edge deployment on NVIDIA Jetson not only reduces latency but also lowers dependency on cloud infrastructure, making the solution more practical and cost-effective for small and medium-sized manufacturers.

V. DISCUSSION

The experimental results validate the effectiveness of the proposed integrated Edge AI vision sensor system. With a defect detection accuracy of 98.4%, a low false positive rate of 1.6%, and a mean inference time of only 64 ms, the system demonstrates clear superiority over traditional manual inspection (82.7% accuracy) and conventional rule-based machine vision (91.2% accuracy). The achieved throughput of 15 parts per minute confirms its suitability for real-time applications in high-speed production lines.

The integration of edge computing on the NVIDIA Jetson platform plays a decisive role in achieving low latency and reducing network dependency. By processing data locally, the system enables immediate anomaly detection and automatic control actions, which significantly minimizes production downtime and material waste. Furthermore, the modular three-layer architecture offers high flexibility and scalability, allowing manufacturers to easily expand the system or adapt it to new product variants with minimal reconfiguration.

However, several practical challenges remain. First, the system's performance can be affected by extreme variations in lighting conditions and complex backgrounds, although robustness above 95% was still maintained in the tests. Second, when product designs or defect types change frequently, periodic retraining or fine-tuning of the deep learning models is required. Third, long-term data management and storage for traceability purposes demand careful consideration of storage solutions and cybersecurity measures in industrial environments.

Despite these limitations, the proposed system provides a cost-effective and practical solution for small and medium-sized enterprises (SMEs) in Vietnam's manufacturing sector, particularly in industrial zones such as Hai Phong. It reduces reliance on skilled labor for inspection tasks while improving product quality and operational efficiency

VI. CONCLUSION

This paper presented an integrated Edge AI vision sensor system for real-time measurement and defect detection in manufacturing automation. The proposed architecture, consisting of a vision sensor layer, an edge AI processing layer deployed on embedded platforms, and a dashboard/control layer, successfully combines high-resolution 2D/3D sensing with deep learning models (YOLO and Mask R-CNN) to deliver accurate, fast, and intelligent inspection capabilities.

Experimental validation on a simulated industrial testbed demonstrated excellent performance, achieving 98.4% defect detection accuracy, 1.6% false positive rate, 64 ms mean inference time, and 15 parts per minute throughput. These results confirm that the system significantly outperforms traditional manual and rule-based vision approaches in both accuracy and efficiency.

The modular and scalable design, along with low-latency edge processing, makes the proposed framework highly suitable for deployment in modern smart factories. It offers a practical pathway for Vietnamese manufacturing enterprises to enhance quality control, reduce inspection costs, and move toward Industry 4.0/5.0 goals.

Future work will focus on improving model adaptability through online continual learning, enhancing robustness under more challenging industrial conditions, and integrating multi-modal sensors (vision + force/position) for more comprehensive process monitoring. The successful implementation of this system is expected to contribute meaningfully to the digital transformation of Vietnam's manufacturing industry.

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