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Article

A YOLOv8-Integrated Educational Platform for Design-Oriented Experiential Learning in Injection Molding Defect Detection

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Abstract: As artificial intelligence and smart manufacturing continue to shape modern industry, vocational education must evolve toward interdisciplinary and practice-oriented learning. To bridge the gap between academic knowledge and industrial AI applications, this study presents an educational YOLOv8-based injection molding defect detection platform. The system modularizes an end-to-end computer vision workflow that includes data collection, labeling, model training, deployment, and real-time inference, using entirely open-source tools such as Python, OpenCV, and PyTorch. On a custom dataset containing bubbles, burn marks, and short shots, the model achieved an mAP@0.5 of 92.5 percent with an average inspection time of less than five seconds per part, confirming both technical reliability and pedagogical feasibility. Classroom implementation demonstrated stronger student engagement, improved comprehension of AI concepts, and enhanced collaboration in problem-solving activities. This open-source and participatory AI workflow not only strengthens technical competence but also reflects a broader cultural shift toward accessible smart-manufacturing education and open design practices, supporting the development of data-driven thinking, interdisciplinary competence, and AI literacy that are essential for future industrial innovation.

Keywords: YOLOv8, Defect detection, Injection molding, Deep learning, Educational system, Real-Time inspection, Smart manufacturing

1. Introduction

In vocational and engineering education, traditional instruction often relies heavily on theoretical exposition, textbook exercises, and simplified simulations. Although these approaches provide essential conceptual foundations, they rarely capture the complexity and uncertainty of real industrial environments. As a result, many students graduate with strong theoretical understanding but lack the practical competence needed to address authentic manufacturing challenges. This disconnect between classroom learning and industrial practice has become increasingly critical in the era of smart manufacturing, where engineers must not only operate machinery but also design, analyze, and optimize intelligent, data-driven systems (Chen et al., 2024; Çelik et al., 2024; Jiao et al., 2025)

Modern industries are rapidly adopting computer vision, deep learning, and automated inspection technologies to improve quality control and production efficiency. Consequently, the ability to understand, implement, and iteratively refine AI-based inspection systems has become a core competency for the next generation of engineers and technicians. However, integrating these advanced technologies into educational settings remains challenging. Barriers include the high cost of industrial equipment, limited access to authentic datasets, and the steep learning curve associated with AI programming and system configuration. As a result, students rarely have opportunities to engage in hands-on, project-based learning experiences that reflect actual industrial workflows.

In this study, the term educational defect-detection system refers to a fully modular, low-cost, open-source platform designed not only to perform defect recognition but also to function as a pedagogical tool for teaching AI workflows. Unlike conventional inspection systems that operate as black-box detectors, the proposed platform enables students to engage with the entire computer-vision pipeline-including data acquisition, image labeling, model training, real-time inference, error analysis, and iterative system refinement. This structure helps learners understand how inspection models are constructed, evaluated, and improved, addressing the current gap in engineering education where students seldom gain exposure to authentic industrial AI processes.

To address these challenges, this study develops an educational platform that transforms the complete workflow of injection molding defect detection into an interactive, experiential, and design-oriented learning environment. Specifically, this study aims to:

1. Translate industrial visual inspection workflows into structured, step-by-step instructional modules suitable for laboratory and classroom use.
2. Reduce barriers to AI adoption in education by implementing the system entirely with open-source tools such as Python, OpenCV, and PyTorch.
3. Provide immersive experiential learning activities in which students participate directly in image acquisition, dataset labeling, model training, hyperparameter tuning, real-time detection, and performance evaluation.
4. Evaluate educational impact through structured classroom observations examining student engagement, conceptual understanding of AI processes, collaborative problem-solving, and system redesign behaviors.

By transforming an industrial-grade AI inspection system into an accessible educational platform, this study introduces an innovative pedagogical model aligned with project-based and experiential learning principles. The system enables students to directly observe how theoretical concepts-such as convolutional neural networks, feature extraction, and performance metrics-translate into tangible engineering outcomes, while the iterative, hands-on nature of the workflow cultivates creativity, critical thinking, and teamwork. This experiential learning process supports the broader digital transformation of engineering education in the era of Industry 4.0 by allowing learners to meaningfully engage with authentic AI-driven inspection practices. Recent studies on injection-molded parts defect detection further emphasize the growing need to integrate advanced visual inspection algorithms into smart-manufacturing education, reinforcing the relevance and timeliness of the present work (Zhang et al., 2024). In addition, it is important to clarify that the system was fully developed by the authors specifically for educational purposes, rather than adapted from any existing commercial or research platform.

2. Materials and Methods

2.1 System Architecture

The proposed educational defect-detection platform consists of two major components: a low-cost hardware setup and a modular software workflow designed specifically for instructional use. The hardware configuration uses a standard 5-megapixel USB camera mounted above a compact inspection fixture that ensures stable sample placement and controlled lighting conditions. The system runs on a personal computer or engineering-grade laptop equipped with a mid-range CPU (Intel i5 or equivalent) and 16 GB of RAM, which is sufficient for real-time inference using CPU-based YOLOv8 processing.

This simplified and inexpensive configuration was intentionally selected to support classroom adoption. Students can assemble the camera rig, adjust working distance and lighting, and trace the signal flow from image capture to detection. The minimal hardware requirement ensures that the platform can be replicated in typical vocational laboratories, enabling individual or group experimentation without reliance on industrial equipment. From a pedagogical perspective, the hardware setup introduces learners to fundamental concepts of imaging design-including viewpoint selection, illumination uniformity, and fixture stability-which are essential in both engineering design and automated inspection tasks.

2.2 Software Framework

The software framework was implemented entirely in Python and integrates OpenCV for image acquisition and preprocessing, and YOLOv8 for real-time defect recognition. YOLOv8 served as the primary detection model and was refined based on insights from lightweight and multiscale CNN studies (He et al., 2025; Ruan et al., 2025; Zhou et al., 2025). The configuration also referenced improvement strategies demonstrated in FSNB-YOLOv8, which enhances feature fusion for industrial defect inspection (Li et al., 2024). Dataset construction and performance evaluation followed methodological guidelines proposed by Ma et al. (2024), ensuring model reliability in an educational environment.

To support instructional goals, the entire workflow was redesigned as a step-by-step learning sequence that mirrors an authentic industrial computer-vision pipeline while remaining accessible to students:

Data Collection and Labeling: I Images of injection-molded parts were captured under uniform LED lighting and annotated using LabelImg. Students participated in data acquisition and labeling to understand how consistent illumination, camera angle, and accurate bounding-box placement influence dataset quality. The final dataset contained approximately 800 images categorized into three common defect types-bubbles, burn marks, and short shots-allowing students to observe how dataset composition affects downstream model performance.

Model Training: The YOLOv8-s model was trained on a personal computer using CPU-based processing. Training images were resized to 640 × 640 pixels, the default YOLOv8 input resolution, ensuring a suitable balance between defect visibility and computational efficiency on educational hardware. Training was performed for 100 epochs with a batch size of 8, enabling students to monitor model convergence, analyze the effects of learning-rate and data-balance adjustments, and compare training logs and accuracy curves. Through this process, learners gained deeper insight into how hyperparameter choices influence machine learning outcomes.

Model Deployment: After training, the optimized model was integrated into a graphical user interface (GUI) developed using Python's Tkinter library. The interface presents live video streams, bounding boxes, defect classifications, and confidence values, enabling students to perform real-time testing with a standard USB camera. By interacting with the deployed system, learners evaluated detection behavior, identified error cases, and explored how lighting, background variation, and sample diversity affect real-world model performance.

2.3 Experimental Setup

The system was evaluated using multiple injection-molded samples exhibiting typical surface defects, including bubbles, burn marks, and short shots (Fig. 1). Quantitative indicators such as detection accuracy, inspection speed, and student task performance were assessed to determine the system's technical performance and classroom applicability.

A total of 24 vocational students participated in two 90-minute laboratory sessions, during which they practiced data labeling, model retraining, and defect testing using the developed educational platform. Learning outcomes were evaluated using a five-point Likert-scale questionnaire that focused on students' engagement, conceptual comprehension, and confidence in applying AI-based inspection tools.

The platform also incorporated a data-logging function that recorded detection counts, accuracy rates, and inspection time, enabling subsequent analysis and structured classroom discussion. This data-driven feedback mechanism helped students connect model behavior with real-world manufacturing inspection concepts, reinforcing understanding of how artificial intelligence can be integrated into quality control processes within smart-manufacturing environments.

(**a**) (**b**) (**c**)

Fig 1. Representative images used in the YOLOv8-based defect detection system. (a)–(c) Common surface defects in injection-molded samples: (**a**) bubble, (**b**) burn mark, and (**c**) short shot. (**d**) A training image captured by a 5 MP USB camera resized to 640 × 640 pixels, showing that the resolution retains sufficient defect detail for model training and educational visualization. Images captured by the authors.

3. Results

The proposed system demonstrated high detection accuracy and strong operational efficiency in both technical evaluation and classroom implementation. The trained YOLOv8 model achieved an average detection accuracy of 92.5%, while inspection time was reduced from approximately 30 seconds per item (manual inspection) to under 5 seconds. These results confirm the system's capability to perform rapid and reliable defect identification using standard computing resources without the need for specialized equipment.

Table 1 summarizes the comparative performance between manual inspection and the proposed system. The automated workflow not only improved inspection accuracy by roughly 15% but also eliminated the need for dedicated manpower at the inspection station, illustrating the practical benefits of integrating AI-assisted inspection into both educational and industrial settings. The obtained accuracy and processing speed align closely with performance benchmarks reported in recent industrial defect detection studies (Gupta et al., 2025; Wu et al., 2024), supporting the validity of the adopted model training and inference methodology. In addition to the Likert-scale responses, qualitative observations showed that students asked more questions and collaborated more actively during troubleshooting, indicating stronger engagement than in earlier laboratory sessions.

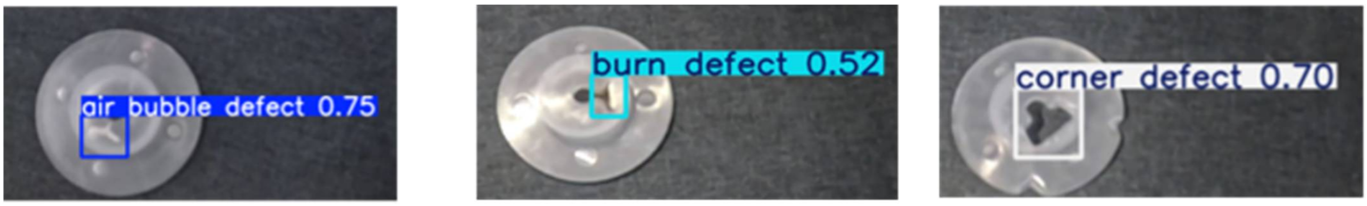
Table 1. Experimental Performance Results.

Evaluation Item	Manual Inspection	Proposed System	Performance Improvement
Inspection Speed	30 sec/item	5 sec/item	+80%
Accuracy Rate	80–85%	92.5%	+15%
Manpower Requirement	1 person/station	0 (maintenance only)	100% reduction

Real-time detection results and annotated images obtained from the system are presented in Fig. 2. The detection interface accurately identified bubbles, burn marks, and short shots, displaying bounding boxes and confidence scores. This visualization allowed students to observe how the YOLOv8 model extracts features and generates classification decisions, thereby strengthening their conceptual understanding of AI inference processes.

Fig. 3 presents the statistical dashboard summarizing inspection outputs, including total inspections, defect ratios, and yield rate. This display served as an effective instructional tool, helping students relate AI-generated results to production-quality indicators commonly used in manufacturing environments. The dashboard supported their interpretation of quantitative data and reinforced the relevance of automated inspection in smart-manufacturing contexts.

During classroom trials, students successfully completed the full workflow-from data labeling and model retraining to real-time deployment-within a single class period. Observational notes and post-activity feedback indicated enhanced engagement, high task completion rates, and greater confidence in applying AI concepts to engineering problems. Learners also reported that the live detection interface and data-analytics dashboard deepened their understanding of automated inspection logic and clarified how AI technologies can assist in quality-control decision-making. Overall, these findings demonstrate the educational value of the proposed system, which provides a hands-on, iterative learning experience aligned with project-based and experiential learning principles while fostering students' development of design reasoning, technical proficiency, and data-interpretation skills.



(a) **(b)** **(c)**

Fig 2. Real-time detection results produced by the proposed YOLOv8-based system. (**a**) Bubble, (**b**) burn mark, and (**c**) short shot, each detected with corresponding confidence levels. The visual interface allows learners to observe how the model interprets surface features during inference, supporting conceptual understanding of AI-based inspection processes.

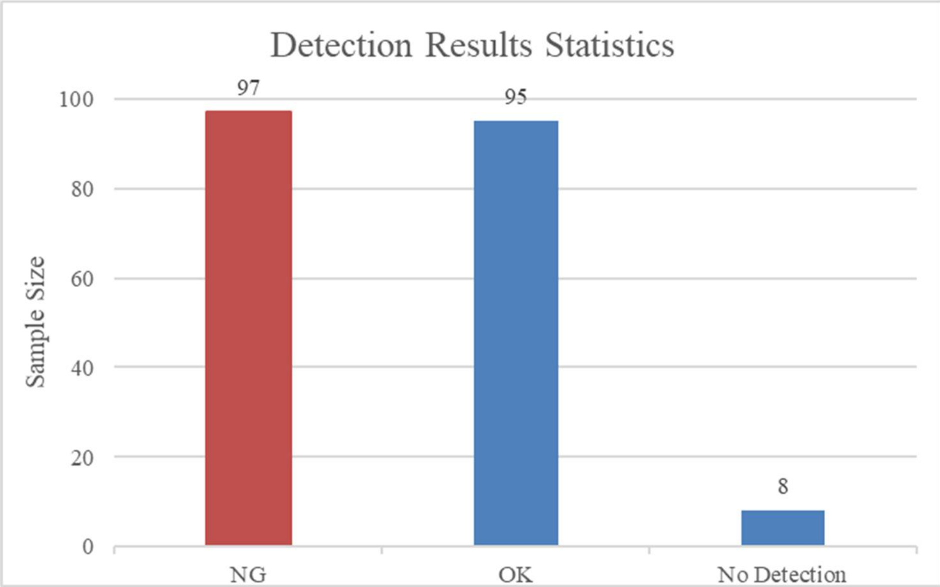


Fig 3. Statistical visualization summarizing inspection outcomes, including total inspections, defect ratios, and yield rate. The dashboard interface helps students interpret AI-generated quantitative results and relate them to common quality-control metrics used in smart-manufacturing environments.

4. Discussion

The proposed defect detection teaching system demonstrates not only strong technical performance but also substantial educational, interdisciplinary, and practical value. The system bridges industrial-grade AI workflows with classroom practice and aligns with recent studies on modular learning systems and AI-based instructional tools (Adhisaputra & Harefa, 2024; Jo et al., 2024; Kang et al., 2025). This section discusses its broader implications for teaching, curricular design, interdisciplinary learning, and industrial collaboration.

4.1 Educational Transformation and Experiential Learning

A key merit of this study is the transformation of a professional AI defect detection system into an instructional platform that enables students to engage directly with authentic industrial workflows. Instead of learning through observation or simplified simulations, learners participate in data collection, image labeling, model training, and real-time inference-activities that foster deeper understanding of computer vision principles and machine learning logic. Traditional vocational and engineering education often struggles to create meaningful connections between abstract concepts and real-world applications; the proposed platform fills this gap by providing a low-cost, hands-on system that mirrors genuine inspection processes.

This experiential approach allows students to observe how misclassifications arise, evaluate model limitations, and iteratively refine solutions. Guided reflection sessions reinforce metacognitive awareness and support long-term retention of knowledge. The platform thus embodies a cultural shift toward open, accessible, and collaborative learning environments consistent with design-driven and student-centered pedagogical frameworks. It positions learners not merely as users of AI tools but as active interpreters and designers of intelligent systems. Because students iteratively redesign datasets, revise lighting conditions, adjust camera angles, and refine model parameters, the platform functions as a design-oriented learning environment where students practice problem framing, prototyping, evaluation, and redesign-key processes in design education.

4.2 Interdisciplinary Integration and Competency Development

Smart manufacturing requires the integration of mechanical engineering, imaging systems, software algorithms, and data analytics. The proposed system exposes students to this multidisciplinary context by providing opportunities to experiment with camera configuration, lighting design, image preprocessing, model hyperparameters, and result analysis. In doing so, students develop cross-domain competencies and learn how decisions in one domain-for example, illumination uniformity or data augmentation-affect outcomes in others.

This interdisciplinary experience strengthens collaborative problem-solving skills and supports the development of the competencies required for Industry 4.0. The team-based, project-oriented tasks also promote communication and coordination-soft skills often underemphasized in conventional technical curricula. The modular structure of the system enables flexible instructional design, allowing instructors to tailor activities to different course levels or disciplinary focuses.

4.3 Modular Design and System Scalability

The system's modular architecture-comprising independent units for image acquisition, data labeling, model training, and visualization-supports both pedagogical flexibility and system scalability. Instructors can adopt selected modules for short laboratory exercises or integrate the full workflow into capstone-style projects. The framework can be easily adapted to detect other defect types, including surface cracks in metals, soldering defects in electronics, or packaging flaws in food manufacturing.

This openness reduces development and maintenance costs and facilitates integration across AI, automation, and quality-control curricula. The modular design also models essential engineering practices such as system abstraction, iterative improvement, and reusable component design-competencies consistent with contemporary design and engineering education.

4.4 Data Visualization and Decision Analytics

A notable feature of the system is its real-time visualization dashboard, which transforms detection results into interpretable charts such as defect ratios, yield rates, and category distributions. This design mirrors industrial Quality Management Systems (QMS) and allows learners to engage with data-driven decision-making in a controlled environment. The visualization tools support the development of data literacy and quantitative reasoning by encouraging students to analyze error patterns, discuss potential root causes, and propose process improvements.

Instructors can leverage these visual outputs to facilitate discussion on system performance, manufacturing tolerances, model optimization, and quality-control strategies. Similar visualization frameworks have been successfully applied to multiscale defect analysis in domains such as 3D-printed ceramic components (Chen et al., 2024), demonstrating the broader applicability of real-time deep-learning inspection systems across educational and industrial settings.

4.5 Educational Outreach and Practical Dissemination

Because the platform is built entirely with open-source tools such as Python, OpenCV, and PyTorch, it can be deployed with minimal financial barriers, supporting its adoption in universities, technical high schools, and workforce-training centers. Its accessible design makes it suitable for AI workshops, STEM outreach initiatives, and academic competitions. With future integration of cloud-based remote access, the system could support online laboratories and inter-institutional collaboration, expanding its reach beyond traditional classroom settings.

This aligns with global trends toward open educational resources (OER) and the democratization of AI learning tools, contributing to the sustainable development of AI-supported learning ecosystems.

4.6 Industry Collaboration and Practical Implications

Although developed for educational purposes, the system holds considerable potential for industrial adaptation. When coupled with production-line equipment, the trained model can support real-time defect detection and feedback control, reducing human error and improving yield. Collaboration with manufacturing partners offers opportunities for students to experience authentic industrial problem-solving and understand the complexities of deploying AI systems in practice.

This collaboration fosters a symbiotic relationship between academia and industry, strengthening workforce development and supporting the creation of AI-oriented talent. Future work should evaluate the system's performance in live production environments and examine its long-term impacts on workforce training, organizational learning, and sustainable manufacturing practices.

5. Conclusions

This study successfully developed and validated a YOLOv8-based defect detection teaching system for injection-molded components, demonstrating both technical feasibility and pedagogical effectiveness. The system achieved high detection accuracy, rapid processing speed, and stable real-time performance using standard computing resources, confirming its suitability for instructional use without requiring industrial-grade hardware. From an educational perspective, the hands-on and modular design enabled students to engage directly with data collection, labeling, model training, and defect inference, thereby deepening their understanding of artificial intelligence, computer vision, and smart-manufacturing workflows. The findings highlight the system's capacity to support experiential learning, promote interdisciplinary competency development, and bridge the gap between academic instruction and industrial practice.

Future work will focus on expanding the training dataset and applying data augmentation techniques to address rare or underrepresented defect categories. Additional research will incorporate multimodal sensing-such as pressure, temperature, and vibration-to enhance detection robustness and model interpretability. System optimization for lightweight edge devices represents another promising direction, supporting broader deployment in field scenarios. Moreover, cloud-based integration will enable remote learning, online laboratories, and multi-institution collaboration. Partnerships with manufacturing enterprises will also be pursued to align instructional outcomes with workforce development needs and to validate the system's applicability in real production environments. Given its modularity and open-source foundation, this educational framework can be readily adapted to other manufacturing domains, supporting interdisciplinary innovation and contributing to sustainable AI talent cultivation in smart manufacturing.

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