

Deep Learning-Based Detection of Shield Presence in Industrial Laser-Marking Applications

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INTRODUCTION & AIM

In industrial electronic assembly processes, ensuring the integrity of components before subsequent operations is critical to avoid defects and equipment damage, as defects directly impact product quality and reliability [1].

In this context, the presence of mechanical shields on chips is essential before laser marking, as the absence of such protection may lead to irreversible damage to the component. Additionally, modern production environments require tight integration between inspection systems and machine controllers. Therefore, this work incorporates real-time communication between the vision system and the main machine controller (PLC) using the Modbus TCP protocol, enabling synchronized decision-making within the production line.

Recent advances in artificial intelligence, particularly deep learning and computer vision, have significantly improved defect detection capability by increasing accuracy, speed, and consistency compared to traditional inspection methods [2][3].

This work proposes the development of an automated visual inspection system based on deep learning to detect the presence or absence of shields in electronic boards. The main objective is to ensure that only fully compliant boards (with all six shields correctly positioned) proceed to the laser marking stage, while defective units are automatically removed from the production line.

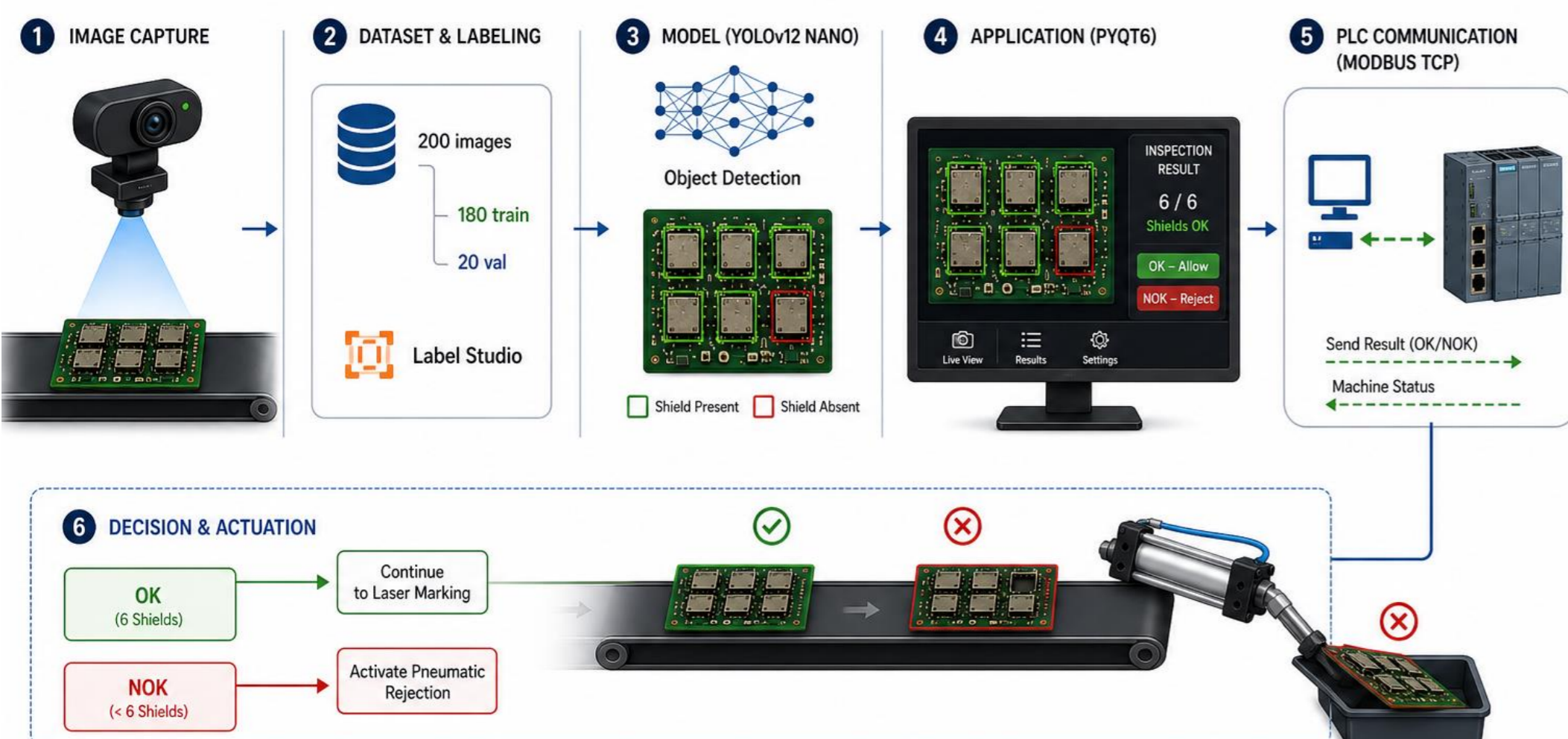


METHOD

The proposed system integrates computer vision, machine learning, and industrial automation. A dataset composed of 200 images was collected under real operating conditions, containing two classes: shield presence and absence. A total of 180 images were used for training and 20 for validation. Image annotation was performed using the Label Studio platform. For object detection, the model YOLOv12 (nano version) was employed due to its low computational cost and suitability for real-time applications. A graphical interface was developed using PyQt6, designed in Qt Designer, enabling real-time visualization of inspection results and system status.

The inspection process operates as follows:

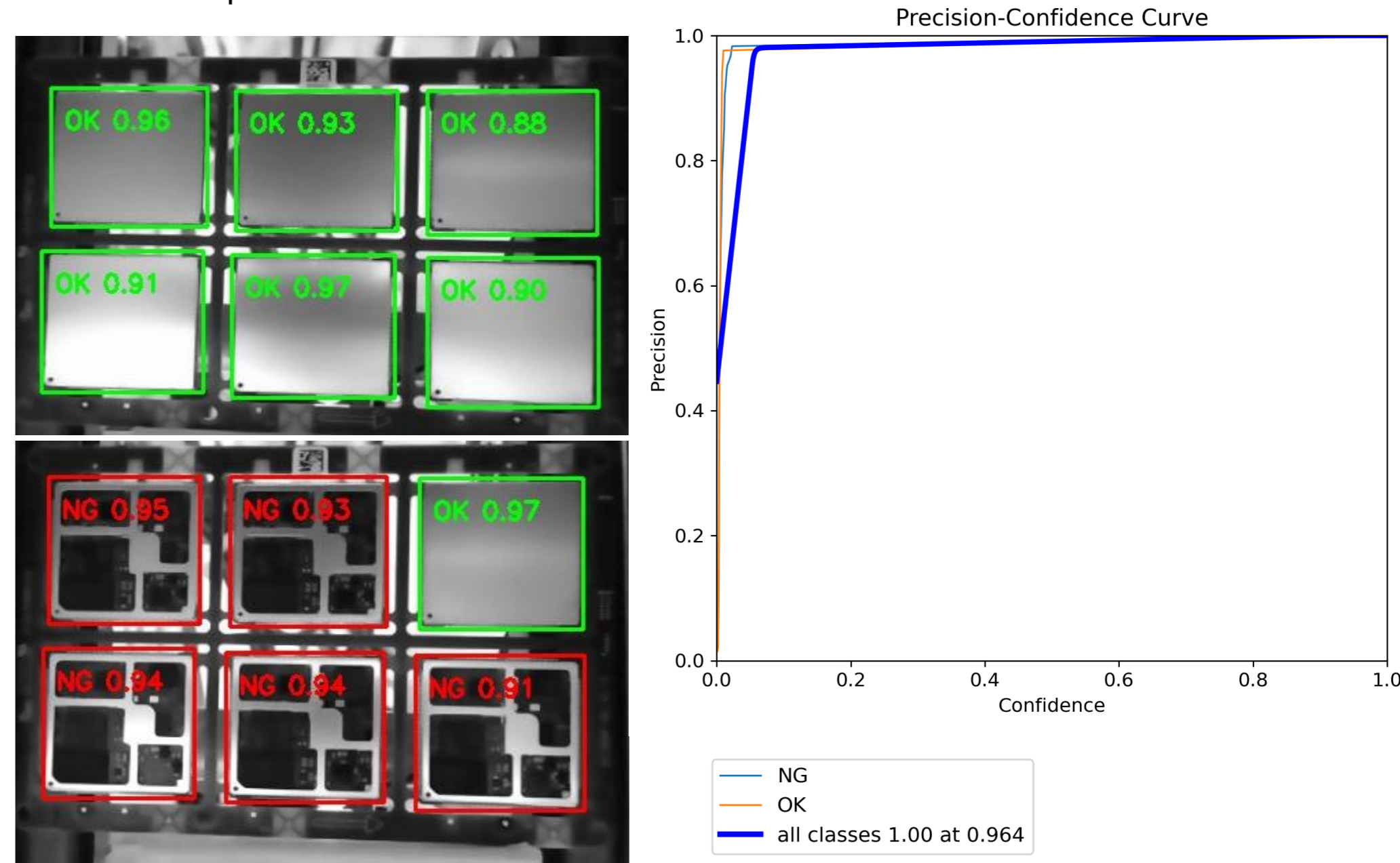
- Each board contains six chips that must have shields.
- The vision system detects and counts the shields.
- If all six shields are present, the board proceeds to the laser marking stage.
- If any shield is missing, a pneumatic system is triggered to remove the board from the conveyor line.



RESULTS & DISCUSSION

The system achieved **96.4% inspection efficiency** under real industrial conditions, even with a limited training dataset. After deployment, **no further damage** to electronic boards was observed during the laser marking process, confirming the effectiveness of the inspection and rejection strategy. The model, based on YOLOv12, presented an average inference time of approximately **0.75 seconds per image**. Including additional processing and communication with the PLC via Modbus TCP, the total inspection cycle remained **below 1 second**, meeting real-time industrial requirements.

The stable communication with the PLC ensured reliable actuation of the pneumatic system for defective board removal. Despite the excellent performance, the reduced dataset may still limit system robustness under varying operating conditions, indicating the need for further data expansion.



CONCLUSION

This work presented an automated visual inspection system based on deep learning for detecting shields in electronic boards. The proposed solution demonstrates effective integration between computer vision and industrial automation, improving process reliability by ensuring that only compliant boards proceed to critical stages. Communication with the PLC via Modbus TCP enables synchronized and autonomous decision-making within the production line. The approach is suitable for real-time industrial environments and highlights the feasibility of deploying lightweight AI models in resource-constrained applications. Furthermore, this work reinforces the potential of deep learning for industrial inspection tasks. Overall, the proposed system represents a practical step toward smarter manufacturing systems.

FUTURE WORK / REFERENCES

Future improvements may include:

- Expansion of the dataset to improve model robustness and generalization
- Implementation of data augmentation techniques
- Deployment on embedded systems (edge computing), such as microcontrollers or industrial PCs
- Integration with predictive maintenance or quality tracking systems (Industry 4.0 context)
- Exploration of model optimization techniques for TinyML applications

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