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AI-Powered Model for Defect Detection and Classification for High-Quality Automotive Manufacturing

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Abstract*:*

This paper presents Detect-iPro, which uses AI to detect defects at the automotive relay box, assign weights, and track faults in real time. The system relies on the highly precise yet fast object detection capabilities of the YOLOv8 model in deep learning and is easily integrated with assembly lines through the use of high-resolution imaging and a convenient graphical user interface. The continuous improvement of processes and regulatory compliance is also possible through automated data logging, as well as real-time feedback, which not only ensures better traceability but also allows for the improvement of the process in question. Thorough testing in factory conditions shows considerable improvements in accuracy, speed, and efficiency, and predetermines new standards in automotive quality control. The paper is completed with a discussion of the system limitations, future research principles, and how AI can transform smart manufacturing.

Keywords: *Defect Detection, Artificial Intelligence, YOLOv8, Quality Control, Automation, Automotive Manufacturing, Industry 4.0, Computer Vision, Deep Learning, Traceability.*

I. INTRODUCTION

There is a paradigm shift in the automotive industry brought about by the harmonization of automation and artificial intelligence. With the world becoming increasingly competitive, manufacturers are under pressure to provide a high-quality experience in terms of quality and safety of cars produced; at the same time, lowering the cost and increasing production speed. Relay boxes are central devices within automotive electrical systems that are significant as regards performance and service of the vehicle, safety, and reliability [2]. The flaws of such elements may result in recalls that are both costly and, not to mention the safety, or even penalties [5] that may be observed in the course of regulation.

Relay box defect detection and classification through human inspectors hava traditionally been based on human inspection, which requires the inspection of thousands of parts each working day under harsh conditions. The human fatigue involved in this manual methodology is inherently curbed by a factor of subjectivity, and the rapid complexity of the modern vehicles [6]. No one has ever needed it more than it is required now because of the need to have consistent, high-speed inspection as well as error-free inspection processes.

Many new generations of intelligent inspection systems that would eliminate these drawbacks are possible due to recent innovations in AI and computer vision, particularly in deep learning [12, 13]. One of these systems is Detect-iPro, an automatic and real-time detection and classification, as well as monitoring system in automotive assembly lines. Using the capability of state-of-the-art deep learning frameworks such as YOLOv8, Detect-iPro not only detects and labels defects in real-time, militarily fast [7, 8, 16], but also lets its users log data in accordance, provide traceability, and provide feedback to operators in real-time.

This paper gives a detailed history of Detect-iPro design, development, and implementation in a production scenario. It also brings out the technical background of the system, the testability of the system, and the effects of the system on automotive quality assurance. Also, the research explores the most recent literature, a current set of practical issues, and future opportunities in need of the implementation of AI-driven inspection in Industry 4.0 manufacturing settings.

To present the details of the study, this paper is organized as follows. Section I introduces the study by describing its background and problem statement. Section II provides a comprehensive review of the related literature. The methodology adopted in this work is explained in Section III. Section IV presents the experimental results along with a detailed discussion of the findings. Finally, Section V concludes the study.

II. LITERATURE REVIEW

Automated defect detection in automotive manufacturing has become increasingly important over the past decade, fueled by advances in computer vision, machine learning, and the growing need for real-time quality assurance in high-speed production environments [1–4]. Traditionally, visual inspection relied on human operators, whose assessments could vary due to fatigue, experience, and attention span. To reduce this dependency, early automated systems used classical image processing techniques, including template matching, edge and height detection, thresholding, and color segmentation. While these approaches partially automated defect detection and reduced human error, they were rigid and required frequent adjustments to handle changes in lighting, part placement, or surface conditions. Consequently, these methods were limited in their ability to scale across different components and defect types [5–8].

The rise of machine learning introduced more adaptable approaches, enabling systems to learn patterns directly from data rather than relying on fixed rules. Convolutional Neural Networks (CNNs) have become a central technology in modern defect detection due to their capacity to extract hierarchical features and classify defects under diverse and challenging conditions [9–12]. CNN-based approaches have been successfully applied to various automotive components, including welded joints, painted surfaces, printed circuit boards, and engine parts, often outperforming traditional methods in both accuracy and robustness [13–16]. By learning from examples rather than predefined features, CNNs can generalize across different defect types and lighting conditions, which is essential for high-speed assembly lines.

Among deep learning approaches, the YOLO (You Only Look Once) family of models, ranging from YOLOv3 to YOLOv8, has emerged as a leading real-time object detection framework for manufacturing applications [7, 8, 16, 17]. YOLO models combine feature extraction, localization, and classification into a single network, enabling fast and accurate detection of multiple defect types simultaneously. This capability is particularly important in automotive production, where high throughput requires rapid inspection without sacrificing precision. End-to-end YOLO pipelines allow manufacturers to inspect multiple components in real time, significantly improving operational efficiency.

Despite these advancements, challenges remain. Most existing systems focus on general defect detection and do not specifically target high-speed relay box inspection, a critical area in automotive electrical systems [18–21]. Many approaches require large, manually annotated datasets, which are costly and time-consuming to create. Furthermore, models trained in one environment may underperform in another due to differences in lighting, part orientation, or surface texture. Many current systems also lack integration with enterprise resource planning (ERP) or manufacturing execution systems (MES), limiting automated logging, operator feedback, real-time traceability, and process optimization [20–24]. Recent research emphasizes the need to link inspection systems with operational intelligence, including energy-efficient sensor networks [23], hybrid routing for industrial IoT [24], cyber-forensic monitoring [25], and secure vehicular networks for manufacturing logistics [26]. These studies collectively highlight the importance of developing inspection systems that not only detect defects accurately but also provide actionable insights, traceability, and connectivity aligned with Industry 4.0 principles.

Detect-iPro addresses these limitations by combining deep learning-based defect detection with automated logging, operator feedback through a user-friendly interface, and ERP integration, enabling real-time inspection, rapid decision-making, and full traceability [13, 20–22]. Its modular design allows deployment beyond relay box inspection, extending to other high-value automotive components, thereby supporting a broader ecosystem of intelligent quality assurance systems. The system's feedback loop allows operators to validate and correct automated decisions, enhancing reliability and adaptability over time. By integrating accurate defect detection with operational intelligence, Detect-iPro provides a practical, Industry 4.0-compliant solution that improves production efficiency, reduces defects, and ensures consistent product quality.

The overall research trends in AI-powered defect detection for automotive manufacturing are shown in Figure 1.

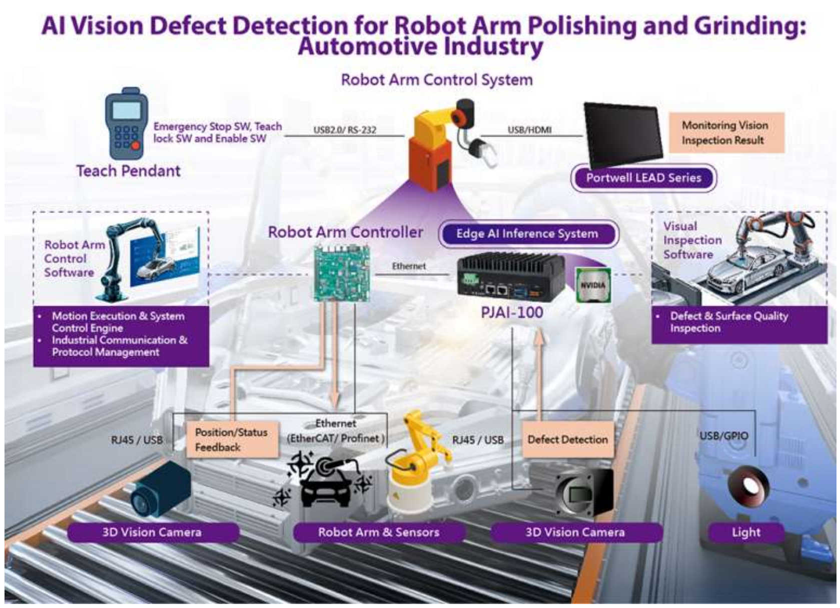

Figure 1: Research trends in AI-powered defect detection for automotive manufacturing

III. RESEARCH METHODOLOGY AND DESIGN

A. System Architecture

Detect-iPro is a real-time, modular, and scalable system for inspection of relay boxes. The proposed system architecture is illustrated in Figure 2. The core components include:

- High-resolution Camera: Mounted above the assembly line, capable of capturing detailed images of each relay box under diverse lighting conditions.
- Processing Unit: A dedicated workstation (Intel i5, 8GB RAM) processes images using the YOLOv8 model, balancing computational efficiency and speed.

- Graphical User Interface (GUI): Provides real-time inspection results to operators, using intuitive visual cues for quick decision-making.
- Automated Logging: Inspection data (status, timestamp, images) is automatically saved in both CSV and JSON formats for traceability and audit purposes.

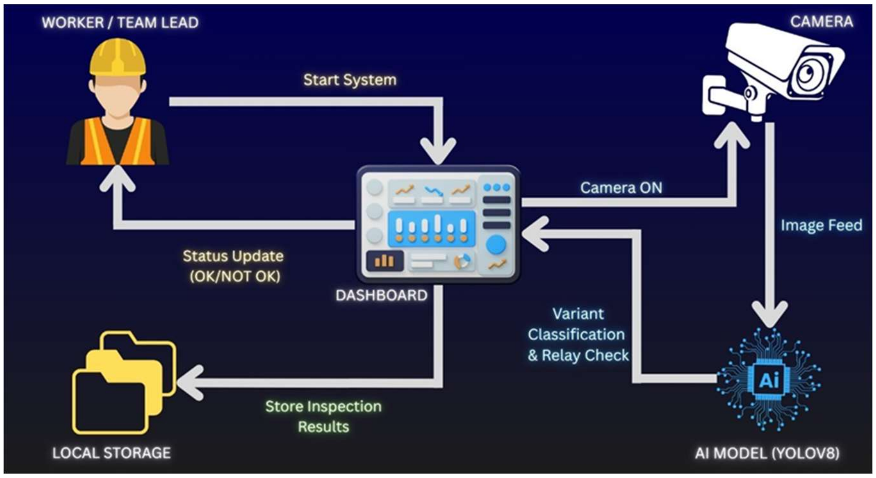

Figure 2: System Architecture

B. Data Collection and Annotation

The richness of the data in terms of variety is important in sound defect determination. More than 3000 shots of relay boxes were taken in different conditions: in bright, in dim, and artificial light, and with the different levels of assembly before assembly of relay boxes. All the relays and potential areas of defect were denoted on each image carefully by placing labels on the image with the help of RoboFlow, as shown in Figure 3. To enhance the competitiveness of the datasets and the resistance of the model, data augmentation, random rotations, scaling, and light changes were employed.

Figure 3: Data Annotation

C. Modal Training

The YOLOv8 was trained on the annotated dataset in 100 epochs [16, 26]. In training, critical performance measures, including accuracy, recall, and mean average precision (mAP), were found to be optimal values so that the model would be robust enough. Cross-validation was also used to introduce K-fold cross-validation to adjust the hyperparameters, which allows the model to predict new data and on-factory environments. The last model has an outstanding mAP of 99, as it has excellent capability to differentiate between the states of the relay box using the terms OK and Not OK.

What is presented in Figure 4 is the Python algorithm that trains the model; this demonstrates the coding structure of the action. Figure 5 is a visual demonstration of the Precision-Confidence Curve as the number of training epochs increases, and the precision changes during the model's training. These results are additionally emphasized by the Precision-Recall Curve, as shown in Figure 6, which shows the balance between precision and recall, and by Figure 7, which indicates that the model can deal with precision and recall under each class.

To measure the capability of the model to predict with significant accuracy, correct class labeling, Figure 8 shows the Recall Curve during the epochs of training, and this shows that the model can remember the correct states, particularly as training advances. The Confusion Matrix in Figure 9 and Figure 10 shows an insight into how the model performs regarding performance on a raw scale and normalized scale, and the accuracy of the predictions made by the model across all the classes.

Figure 11 is the Labels Correlogram, which indicates the co-occurrence of classes, and Figure 12 gives the Distribution of Labeled Data per Class, which again reiterates the balanced dataset on which it was trained and therefore no class underrepresentation.

Through these values, the training process of the model is completely represented, and the findings indicate that the YOLOv8 model is highly optimized to be used in the objective world detector in defect detection on the automotive relay box.

```python
from ultralytics import YOLO


model = YOLO('yolov8s.pt')


results = model.train(
    data='data.yaml',
    epochs=100,
    imgsz=640,
    batch=16,
    patience=10,
    optimizer='SGD'
)

print("Training completed. Best model saved to: runs/detect/train/weights/best.pt")
```

Figure 4: Python script for Model Training

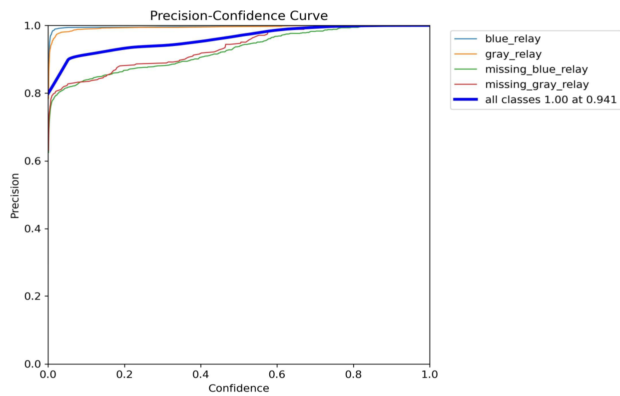

Figure 5: Precision-Confidence Curve over Training Epochs

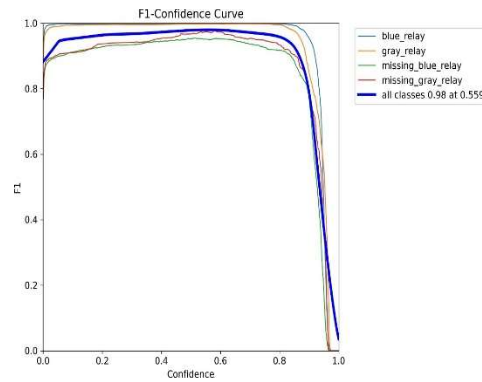

Figure 6: Model Balance between Precision and Recall

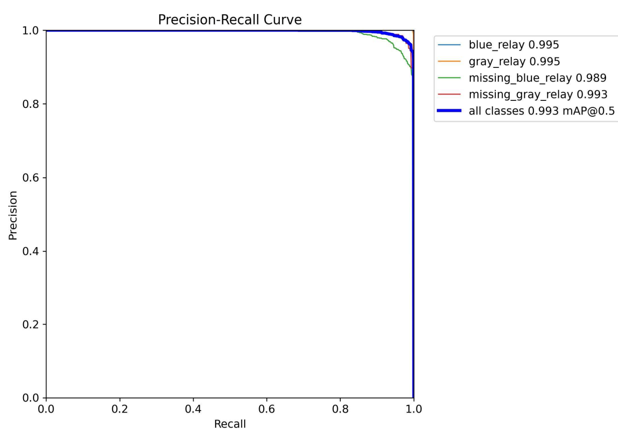

Figure 7: Precision Recall Curve for All Classes

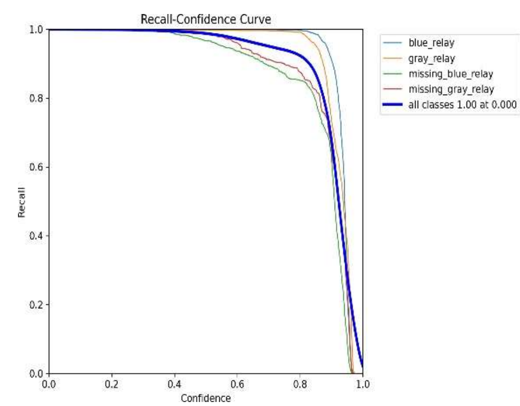

Figure 8: Recall Curve over Training Epochs

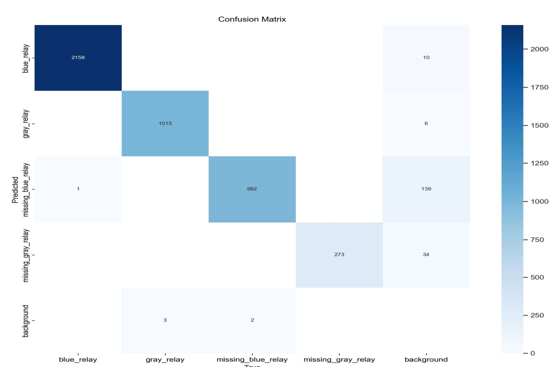

Figure 9: Raw Confusion Matrix of Model Predictions

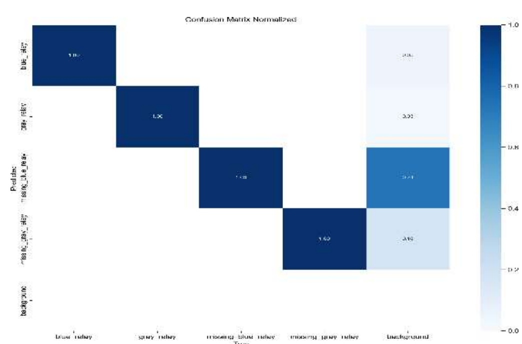

Figure 10: Normalized Confusion Matrix Class-wise

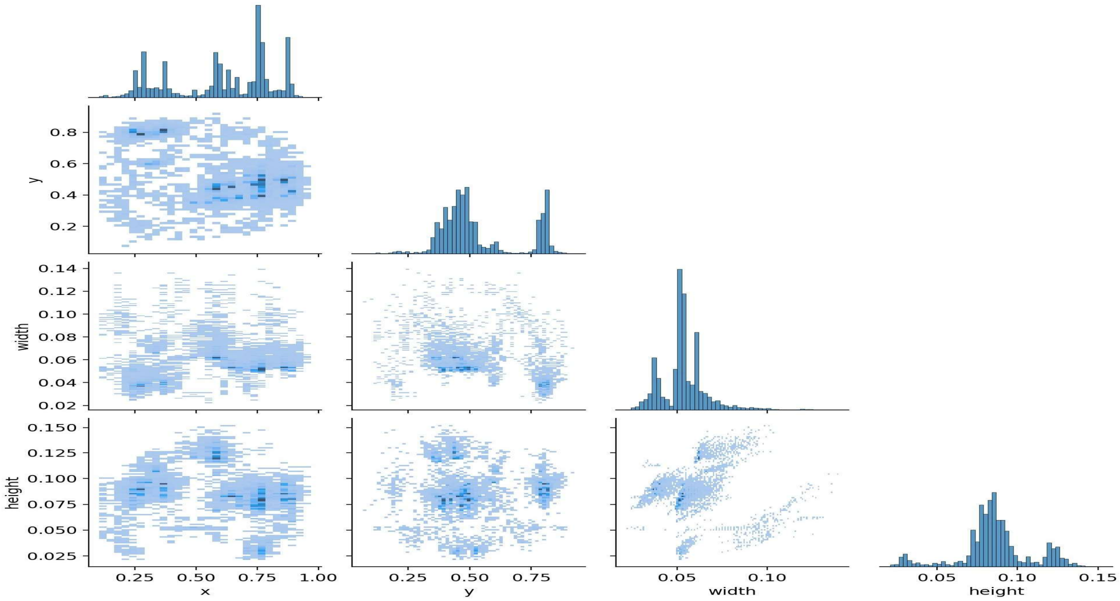

Figure 11: Labels Correlogram Showing Class Co-occurrence

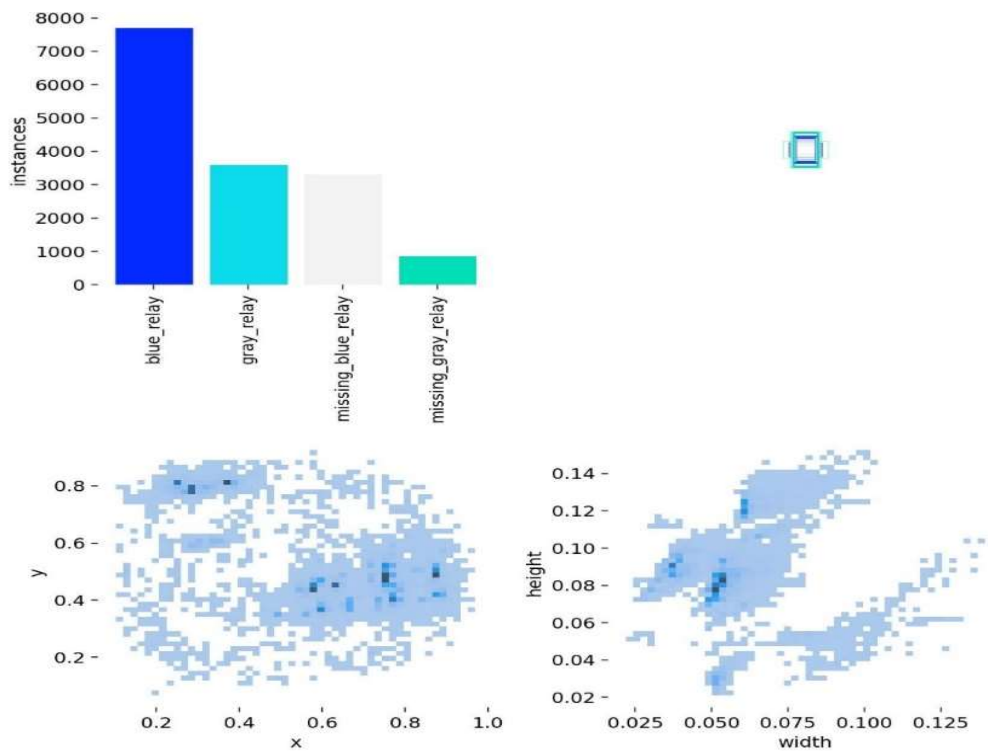

Figure 12: Distribution of Labeled Data per Class

D. Integration and Workflow

The system was integrated into an actual automotive assembly line at IMC Toyota. The real-time workflow is shown in Figure 13 and is as follows:

- Each relay box passes beneath the camera, which captures a high-resolution image.

- The YOLOv8 model processes the image and classifies the box.
- The GUI displays the status (green: OK and red: Not OK) along with bounding boxes around detected defects, as shown in Figure 14.
- Operators receive immediate feedback and can halt the line or perform corrective actions as needed.
- All results are logged automatically for quality tracking and future audits.

Figure 13: Schematic diagram of the Detect-iPro system architecture

IV. RESULTS AND DISCUSSION

The performance of Detect iPro was evaluated in terms of detection accuracy and inspection speed and was compared with conventional manual inspection. The system achieved a detection accuracy of 99.3 percent, which is significantly higher than the 85 percent accuracy obtained through manual inspection. In addition, the average inspection time per relay box was reduced from 10 seconds in manual inspection to 1.5 seconds using the AI-driven approach. This substantial reduction in inspection time resulted in improved throughput and overall operational efficiency. A comparative summary of inspection performance is presented in Table 1.

Table 1: Performance Comparison between Manual and AI-driven Relay Box inspection.

Metrics	Manual Inspection	Detect-iPro
Average Inspection Time (sec)	10	1.5
Detection Accuracy (%)	85	99.3
Error Rate (%)	15	< 2

The implementation of Detect iPro significantly reduced inspection errors, with misidentification rates falling below 2 percent, thereby minimizing the likelihood of defective relay boxes progressing to subsequent stages of the assembly line. Furthermore, all inspection data were recorded automatically, creating a reliable digital audit trail. This capability supports internal process optimization and ensures compliance with quality standards and regulatory requirements. The availability of complete inspection records also enhances traceability, which is essential for continuous improvement initiatives and external quality audits.

From an operational perspective, the adoption of Detect iPro reduced dependence on manual inspection, leading to savings in both labor costs and inspection time. The decrease in downstream rework, warranty claims, and product recalls contributed directly to cost reduction and improved production reliability. These improvements also had a positive impact on brand reputation by ensuring consistent product quality and reducing the risk of defective products reaching customers.

The system demonstrated several strengths, including high detection accuracy, rapid feedback to operators, and smooth integration with existing assembly line infrastructure and enterprise resource planning systems. The automated digital record keeping further enabled effective traceability and data-driven analysis. However, certain limitations were observed during implementation. The current setup relies on a single fixed-angle camera, which may limit the detection of concealed defects. Incorporating multi-angle or three-dimensional vision systems could improve inspection coverage. In addition, system performance may be influenced by extreme lighting variations, suggesting the need for adaptive lighting solutions in future implementations.

Future enhancements to Detect iPro may include the integration of multi-angle imaging systems, predictive maintenance capabilities, and deployment across additional automotive components. Owing to its modular and scalable architecture, the proposed framework can be extended beyond relay box inspection to other high-value manufacturing applications. These developments would further strengthen the role of AI-driven inspection systems in smart manufacturing environments.

Figure 14: GUI output for relay box inspection with bounding boxes and defect classification

V. CONCLUSION

This study proposed Detect-iPro, an intelligent defect detection and quality assurance system developed for automotive manufacturing applications. The framework combines deep learning–based visual analysis, real-time image acquisition, and automated feedback processes to improve inspection reliability and operational efficiency in smart manufacturing environments. By reducing manual intervention, the system enhances inspection consistency and supports data-driven quality control.

The effectiveness of the proposed approach was validated through a practical deployment on an active production line. Experimental observations confirm that Detect-iPro delivers notable gains in inspection speed, cost reduction, and defect traceability, while maintaining uninterrupted production flow. Early identification of manufacturing defects enables timely corrective actions, minimizing rework and material waste across assembly stages.

Evaluation results further indicate that the system achieves robust detection performance under real-world conditions, including variations in illumination, component geometry, and surface characteristics. In comparison with traditional inspection techniques and conventional vision-based systems, the proposed solution demonstrates improved adaptability and scalability, making it suitable for large-scale industrial implementation.

Although the system shows strong performance, certain limitations remain. Future enhancements should aim to expand defect category coverage, improve model generalization for diverse components, and increase system flexibility across different manufacturing environments. Additional research may also explore the integration of edge computing, predictive maintenance, and self-learning mechanisms to further strengthen intelligent quality assurance capabilities. Overall, the findings confirm that Detect-iPro provides a practical and effective AI-enabled inspection framework for automotive manufacturing aligned with Industry 4.0 principles. The system establishes a foundation for next-generation automated quality control solutions. Future work will focus on hardware-in-the-loop validation, multi-plant deployment, and tighter integration with manufacturing execution systems, ensuring long-term industrial applicability and reliability.

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