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Development of a Cyber Physical System in Real Time Bolt Defect Detection using Machine Learning based Automated Quality Control

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ABSTRACT: This paper presents the development of a cyber-physical system for real-time bolt defect detection and quality control using machine learning and computer vision. The system employs the YOLOv8 object detection model to accurately identify and classify various bolt defects, such as cracks, rust, deformation, and missing bolts, from continuous video streams. A key innovation in this project is the deployment of the trained YOLOv8 model on a Raspberry Pi, enabling real-time inference and decision-making at the edge without reliance on cloud infrastructure. The bolts are monitored as they move along a conveyor belt, and based on the classification results, GPIO-controlled actuators sort defective and non-defective bolts into separate bins. The system also incorporates temporal analysis across video frames to improve detection stability and reduce false positives caused by motion blur or occlusions. The proposed system demonstrates a scalable and cost-effective solution for automated quality inspection, aligning with Industry 4.0 goals and offering a practical step towards intelligent manufacturing.

KEYWORDS: Bolt defect detection, YOLOv8, Raspberry Pi, Cyber Physical System, video processing, defect classification.

I. INTRODUCTION

Ensuring product quality in modern manufacturing requires faster and more reliable inspection methods, especially for bolts, where defects like cracks, rust, deformation, or missing parts can lead to safety issues and machine failure. Manual inspection is slow and inconsistent, so this work introduces a real-time bolt defect detection system using the YOLOv8 vision model. It identifies not just the presence of bolts but also classifies specific defect types, while temporal frame analysis helps reduce false detections during motion.

The system runs on a Raspberry Pi for low-cost, on-device processing, capturing live video from a conveyor setup and automatically sorting defective bolts through GPIO-controlled actuators. A web dashboard provides live monitoring, logs, and defect analytics for operators. A custom dataset collected under real factory conditions was used for training. By combining AI vision, edge computing, and automated sorting, this project delivers a compact Industry 4.0-ready solution for improving industrial quality control.

II. LITERATURE SURVEY

Research on defect detection using deep learning has grown rapidly across industries. Yang et al. [1] and Jiao et al. [4] showed that CNN-based models can accurately detect small defects in fast-moving environments such as conveyor systems and power transmission towers, achieving high accuracy even under non-uniform speeds and complex backgrounds. Azari et al. [6] highlighted the role of transfer learning in predictive maintenance, while Ling and Isa [8] reviewed PCB defect detection trends. Thai et al. [15] demonstrated real-time CNN-based classification of coffee bean defects with over 99% accuracy.

YOLO-based solutions have also shown strong performance. Shinde et al. [2] used YOLOv3/v4 for wafer defect localisation, and Moon et al. [3] improved sewer defect detection by combining YOLO-like spatial reasoning with text analysis. Improved YOLOv7 variants were proposed for steel surfaces [5], tobacco stems [7], wood defects [12], and electronic components [16]. YOLO with Deep-SORT enabled pipe defect tracking [18], while LE-YOLOv5 improved steel inspection speed [14]. Pothole detection using YOLOv8 was achieved with 95.8% accuracy [20], and CCG-YOLOv7 formalized binary detection evaluation for robust industrial use [21].

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Other lightweight or hybrid models have been explored. Enhanced Nano-Det models improved foreign object detection on conveyors [9], and CPS-based systems enabled real-time surface quality inspection [10]. Attention-driven cascaded models improved bolt defect classification [11], while machine learning-based predictive maintenance was demonstrated on yarn machines [13]. IoT-enabled systems were developed for conveyor roller monitoring [17], acoustic-based fault detection [19], tomato quality inspection [22], multi-crane visual sorting with virtualised PLCs [23], and high-precision steel defect detection using GDM-YOLO [24]. Cross-domain R-CNNs improved insulator defect detection under varying conditions [25], and gaze-aware scene recognition models achieved high accuracy for sports applications [26].

III. MATERIALS USED

The project uses a Raspberry Pi 4 as the edge-computing unit to run real-time YOLOv8 inference, along with a high-resolution camera mounted above a conveyor to capture bolt images. A custom-built conveyor system moves bolts for inspection, and a GPIO-controlled actuator (servo/pneumatic pusher) handles automatic sorting. Stable lighting is provided using LED illumination to reduce shadows and motion blur. The system also includes power modules, wiring, mounts, and housing for safe operation. A web dashboard, developed using backend services, enables real-time monitoring, logging, and analytics. Finally, a custom annotated bolt dataset forms the core training material for the YOLOv8 defect detection model.

IV. HARDWARE

The hardware layout shown in Figure 1 demonstrates how different electronic and mechanical components work together to form a complete real-time bolt inspection and sorting system. At the heart of the setup is the Raspberry Pi 4, which acts as the main processing unit responsible for running the YOLO-based defect detection model. Connected to the Pi through a USB interface is the TVS WC-103 HD webcam, mounted above the conveyor to continuously capture clear video frames. These images are processed instantly by the Pi to identify good and defective bolts as they move along the conveyor.

To communicate with external controllers, the Raspberry Pi is linked to a CP2102 USB-to-TTL UART converter, allowing reliable serial communication. This interface ensures that the detection results are passed smoothly to the Arduino Uno, which handles all motor-related operations shown in the figure. The Arduino is directly connected to the L293D Motor Driver Shield, which provides the necessary current amplification and directional control for both the conveyor motor and the sorting mechanism.

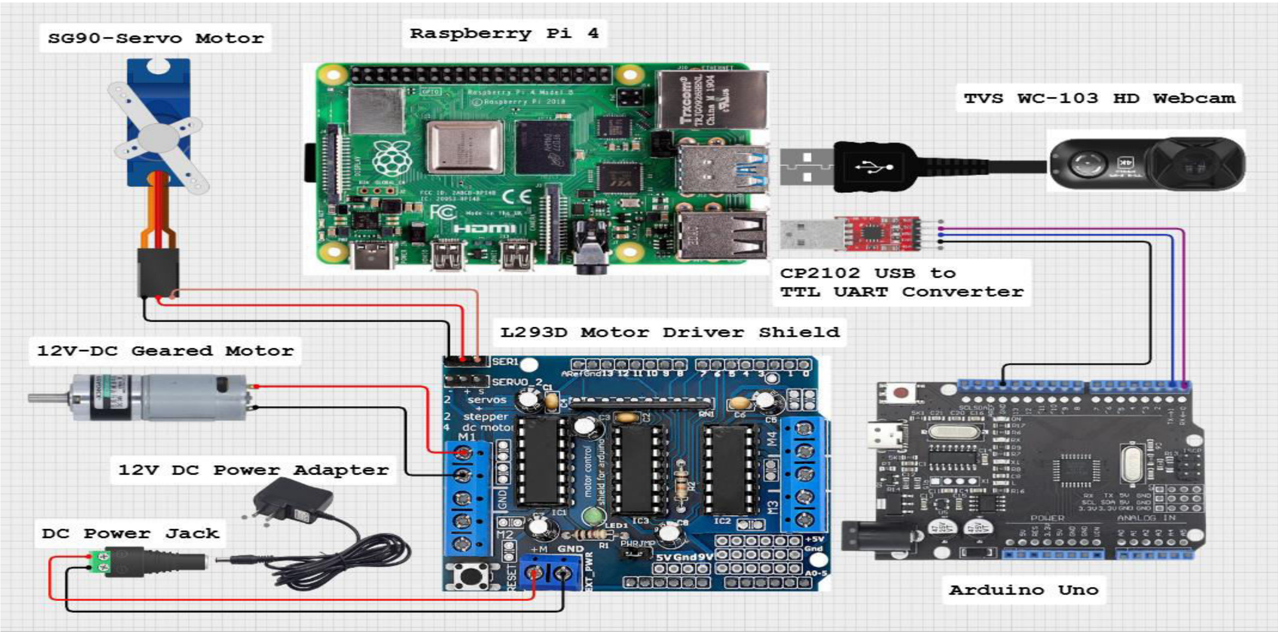

Fig. 1 Circuit diagram of Bolt defect detection

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The conveyor is powered using a 12V DC geared motor, chosen for its ability to deliver stable torque at controlled speeds. As shown in the diagram, the motor is supplied using a 12V DC power adapter connected through a standard DC jack, which feeds the L293D shield. This ensures uninterrupted power delivery during continuous conveyor operation. The motor's wiring, including power and control lines, follows the arrangement shown to maintain smooth and consistent forward motion of bolts.

To automate the sorting of defective bolts, the setup includes an SG90 servo motor, clearly connected to the motor driver in the figure. The servo is responsible for making quick directional movements to push or divert faulty bolts into a separate section. Its lightweight structure and fast response time make it ideal for real-time actuation triggered by detection results coming from the Raspberry Pi.

The Arduino Uno plays a crucial bridging role in the system. While the Raspberry Pi focuses on vision processing, the Arduino ensures accurate execution of low-level motor commands. It receives serial instructions through the CP2102 module and drives both the DC motor and servo using PWM and control signals routed through the L293D shield. This division of responsibilities ensures that image processing and motor control do not interfere with each other, enabling stable overall performance.

The wiring layout shown in the figure reflects a well-organised integration of power distribution, signal routing, USB peripherals, and motor interface connections. Each component-camera, Raspberry Pi, CP2102 converter, Arduino Uno, L293D motor shield, DC motor, and servo works together as a synchronised cyber-physical platform. This combination of computing, sensing, and actuation creates a fully functional real-time inspection system capable of detecting defects and sorting bolts automatically with high reliability.

V. METHODOLOGY

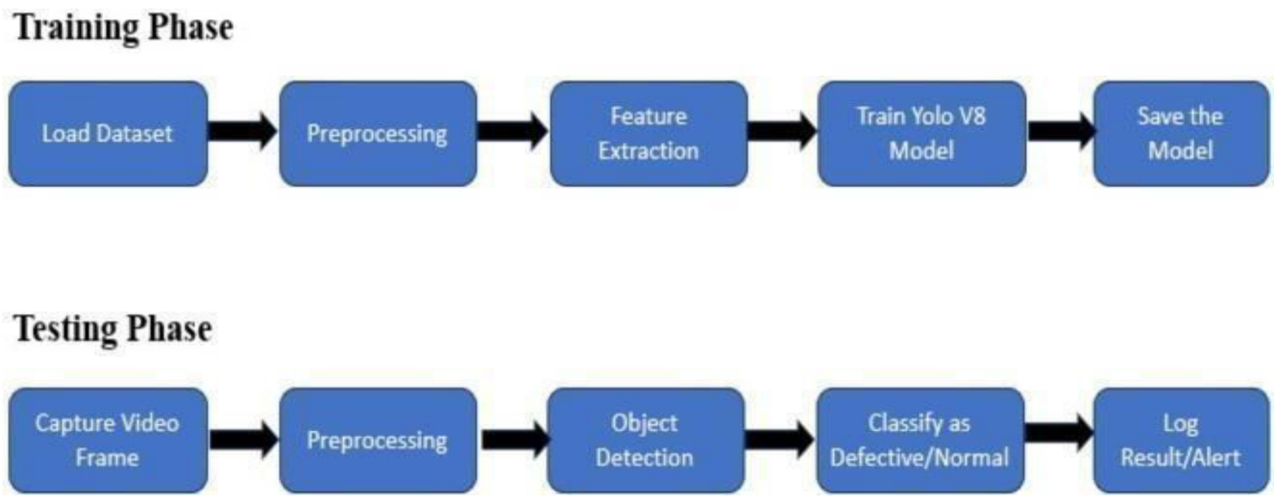

Fig. 2 Methodology of our project

A. Training Phase

- Load Dataset: Collect or use datasets (e.g., SBSDD, Screw Dataset, or custom industrial bolt) with labelled bolt defects such as rust, crack, missing, or deformation.
- Preprocessing: Normalise image resolution, apply augmentation (rotation, contrast, blur), and convert annotations to YOLO format.
- Feature Extraction: Use tools like LabelImgor and Roboflow to draw bounding boxes and label defect types.
- Train YOLOv8 Model: Use the annotated dataset to train the YOLOv8 model on bounding box regression and defect classification.
- Save Model: Export the trained weights (best.pt) for use in inference during real-time defect detection.

B. Training Phase

- Capture Video Frame: Acquire live frame from industrial video feed/testing footage.
- Preprocessing: Resize frames and normalise to match the training dataset conditions.
- Object Detection (YOLOv8): Pass the frame to the trained YOLOv8 model to detect and classify bolts and

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their defects.

- Classify as Defective/Normal: Evaluate detected objects and categorise each as normal or defective based on the model's predictions.

VI. RESULTS AND ANALYSIS

This chapter summarises the performance of our real-time bolt defect detection system built using YOLO-based deep learning models. We evaluated YOLOv8, YOLOv9, YOLOv11, and YOLOv12 on a custom industrial dataset, analysing their training behaviour, validation stability, and detection accuracy. Metrics such as precision, recall, mAP50, mAP50-95, and loss curves were used to understand how well each model localised and classified defects. After comparing accuracy, speed, and consistency, YOLOv8 emerged as the most reliable architecture, offering strong generalisation and stable learning. Overall, the results show that the system can deliver fast, accurate, and automated bolt defect detection suitable for real industrial use.

A. YOLOv8 Training Results

Fig. 3 shows the YOLOv8 model trained for 100 epochs on the custom bolt defect dataset, where the training curves clearly indicate steady improvement in bounding-box regression, classification accuracy, and overall detection quality. The box loss, classification loss, and DFL loss consistently decrease, showing that the model becomes more accurate and confident with each epoch. Although validation loss fluctuates early due to dataset variation, it gradually stabilises, confirming good generalisation without overfitting. Precision and recall rise above 0.90, indicating reliable detection with minimal false positives. Strong gains in mAP50 and mAP50–95, both showing upward trends above industry-acceptable levels, demonstrate that YOLOv8 performs well across both standard and stricter IoU thresholds, making it suitable for precise industrial defect inspection.

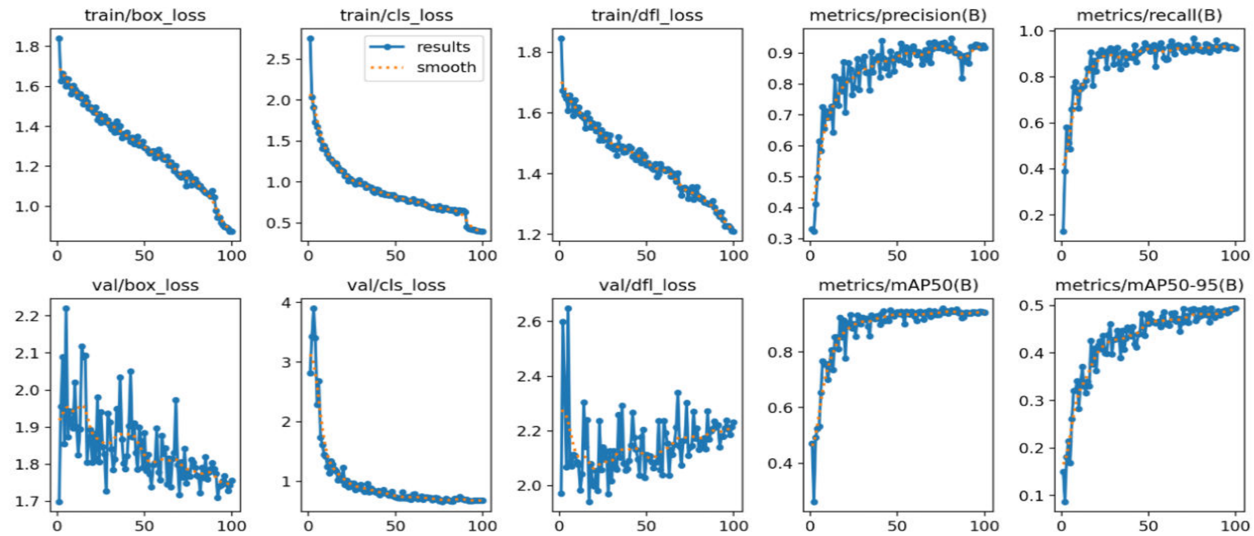

Fig. 3 YOLOv8 training curves showing box loss, classification loss, DFL loss, precision, recall, mAP50, and mAP50–95 across 100 epochs

B. YOLOv9 Training Results

Fig. 4 shows the YOLOv9 model trained for 25 epochs on the same bolt defect dataset, where the training curves indicate fast and smooth convergence. All major losses—box loss, classification loss, and DFL loss—drop consistently, reflecting improved localisation and clearer separation of defect categories. Although validation losses fluctuate initially due to dataset variability, they stabilise after a few epochs, showing good generalisation without overfitting. Precision and recall steadily improve, reaching around 0.85 and 0.90, indicating reliable defect identification with minimal false detections. Both mAP50 and mAP50–95 show positive upward trends, confirming strong performance under standard and strict IoU conditions. Overall, YOLOv9 demonstrates efficient learning and quicker convergence, making it suitable for real-time bolt defect detection where faster training and solid generalisation are preferred.

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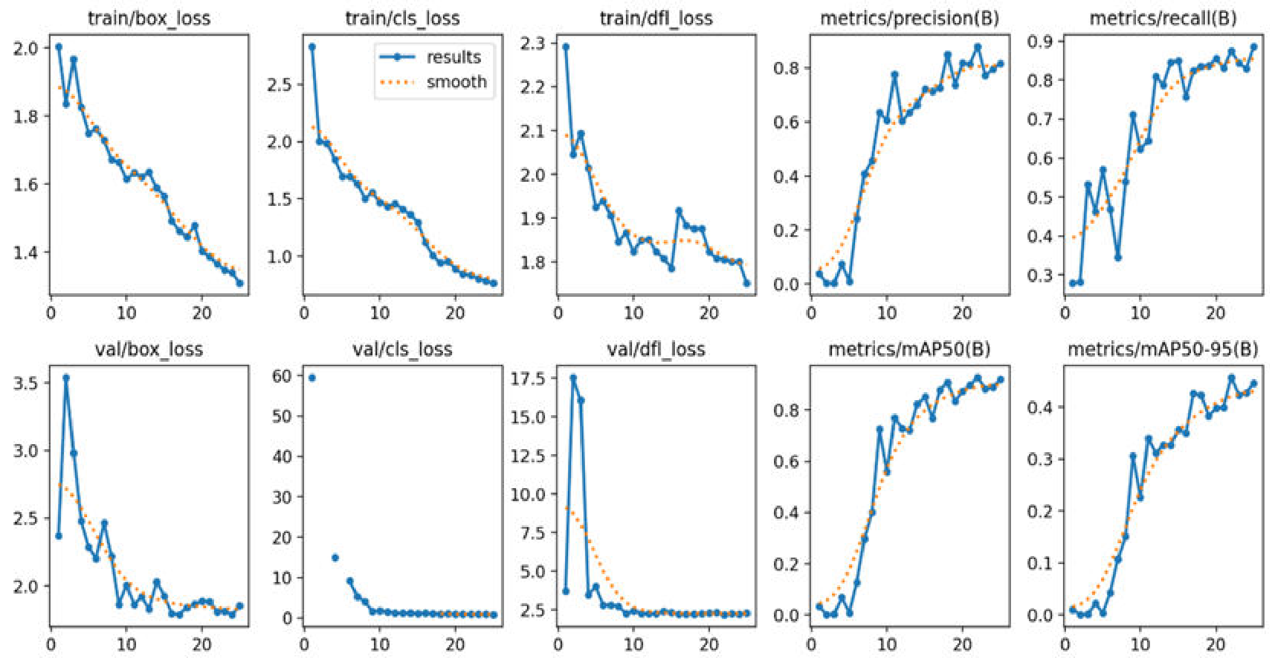

Fig. 4 YOLOv9 training curves showing box loss, classification loss, DFL loss, precision, recall, mAP50, and mAP50–95 across 25 epochs.

C. YOLOv11 Training Results

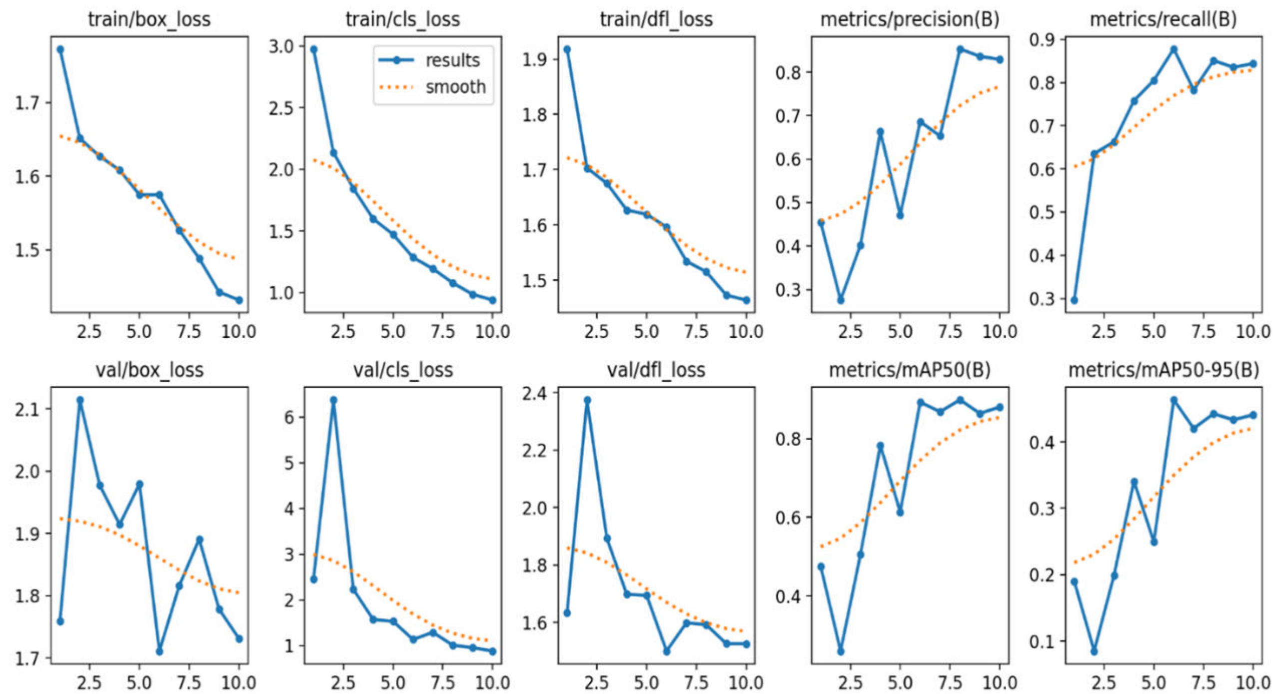

Fig. 5 YOLOv11 training curves showing box loss, classification loss, DFL loss, precision, recall, mAP50, and mAP50–95 across 10 epochs.

Fig. 5 shows the YOLOv11 model trained for 10 epochs, where the training curves display smooth and consistent loss reduction. Thanks to its improved backbone and optimized attention modules, YOLOv11 converges quickly while maintaining strong accuracy. All training losses-box, classification, and DFL-drop steadily, indicating better

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localization, clearer defect classification, and refined boundary learning. Validation losses show minor early fluctuations but stabilize well, confirming good generalization on unseen bolt images. Precision and recall rise above 0.80, and both mAP50 and mAP50–95 show strong improvement, reaching close to 0.85–0.90, which highlights accurate defect localization even under stricter IoU thresholds. Overall, YOLOv11 demonstrates fast convergence and reliable performance, making it a promising choice for real-time bolt defect detection in cyber-physical systems.

D. YOLOv12 Training Results

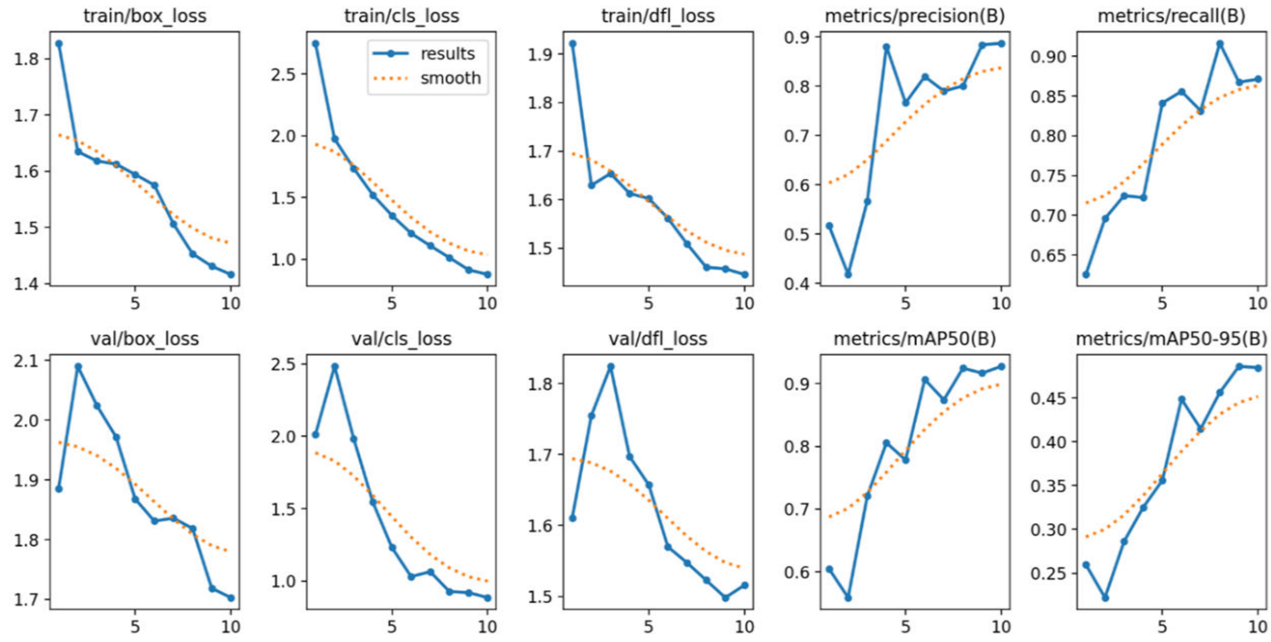

Fig. 6 YOLOv12 training curves showing box loss, classification loss, DFL loss, precision, recall, mAP50, and mAP50–95 across 10 epochs.

Fig. 6 shows the YOLOv12 model trained for 10 epochs, where the training curves demonstrate smooth and consistent reductions in box loss, classification loss, and DFL loss, indicating strong learning of defect localization and class separation. Validation losses fluctuate slightly early on but steadily decrease, showing good generalization without overfitting. Precision rises to around 0.85–0.90 with recall reaching nearly 0.90, meaning the model avoids false positives while correctly detecting most defects. mAP50 increases close to 0.90, and mAP50–95 reaches around 0.45–0.50, reflecting solid performance even under strict IoU thresholds. Overall, despite being an experimental variant, YOLOv12 converges quickly and delivers competitive accuracy, making it suitable for real-time bolt defect detection in cyber-physical systems.

E. Comparative Analysis of YOLO Models

To identify the most efficient model for real-time bolt defect detection in a Cyber-Physical System (CPS), four state-of-the-art YOLO architectures -YOLOv8, YOLOv9, YOLOv11, and YOLOv12 were systematically trained and evaluated using an identical dataset, preprocessing pipeline, and hyperparameter settings. This uniform setup ensures that the performance comparison is fair and unbiased across all models. Each architecture was trained for 25 epochs to maintain consistency and to observe how well the models converge within the same computational budget. The evaluation focused on critical metrics such as Precision, Recall, mAP@50, and mAP@50-95, which collectively reflect the model's detection accuracy, reliability, and overall robustness in distinguishing between good and defective bolts. The detailed numerical comparison, along with brief remarks summarising each model's behaviour and performance characteristics, is presented in the Table. 1, providing a clear insight into which YOLO variant is best suited for high-speed industrial CPS deployments.

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Table. 1 Comparison of YOLO Models for Bolt Defect Detection

Model	Training Epochs	Precision (P)	Recall (R)	mAP@50	mAP@ 50-95	Remarks
YOLOv8	25	**0.89**	**0.90**	**0.88**	**0.45**	Best balance of speed & accuracy; stable convergence
YOLOv9	25	0.83	0.87	0.84	0.42	Good accuracy but slightly higher loss and fluctuation in validation
YOLOv11	25	0.88	0.86	0.87	0.44	Consistent results; fast convergence but limited epochs
YOLOv12	25	0.91	0.88	0.90	0.46	Improved precision; stable close toyolov8

F. Real Time System Output

The Fig. 7 shows the Bolt Fault Detection System interface in its initial state before any image is captured or processed. At this stage, the system awaits user input to select the camera, set the detection mode, and begin the capture process. No bolt image is displayed in the preview pane, and all detection counters remain at zero. The Arduino communication panel is inactive, indicating that no hardware interaction has been initiated. This figure represents the system's idle and ready-to-start condition.

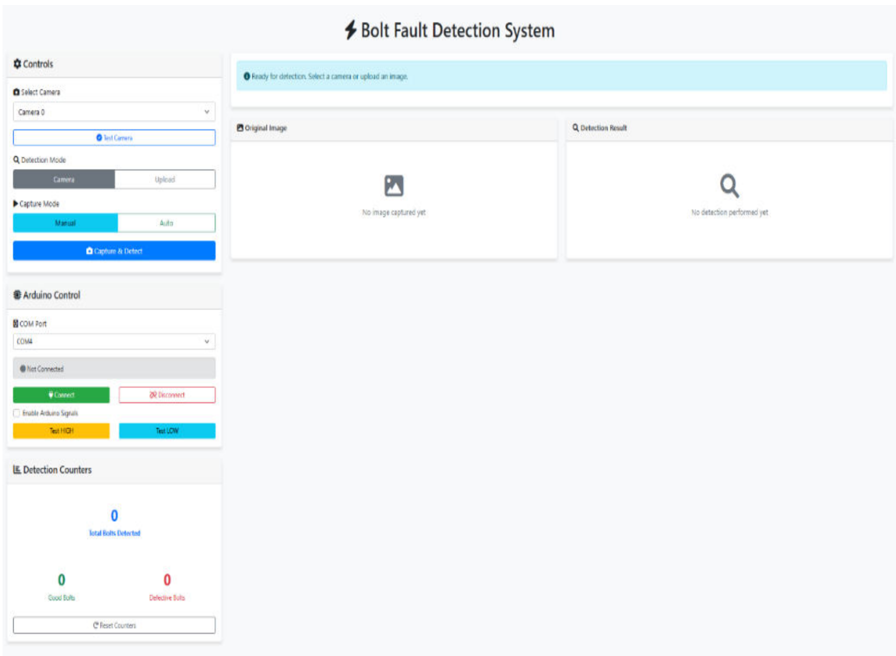

Fig. 7 Bolt Fault Detection System – Before Detection

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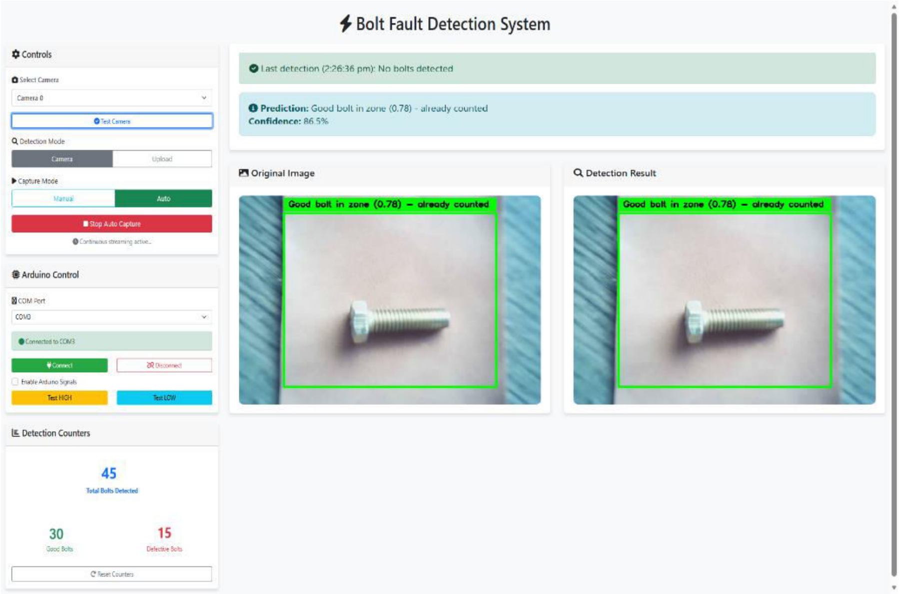

Fig. 8 Bolt Fault Detection System – Good Bolt Detection Output

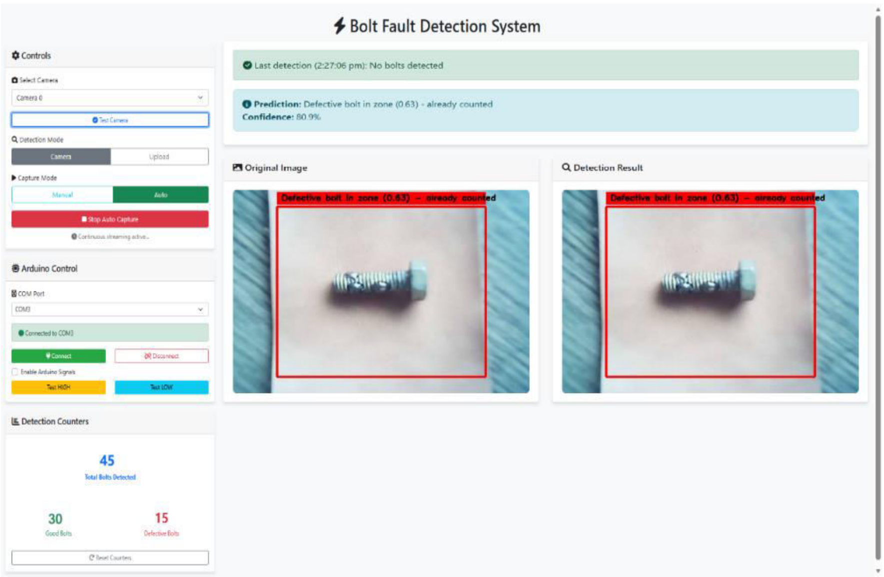

Fig. 9 Bolt Fault Detection System- Defective Blot Detection Output

The Fig. 8 illustrates the detection output when the system identifies a good bolt. The bolt is highlighted with a green bounding box, and the prediction confidence is displayed clearly at the top of the image. Both the original and processed frames are shown side-by-side for verification. The Arduino module shows an active connection, ensuring proper communication with the sorting hardware. The detection counters update automatically to reflect the number of good bolts successfully classified.

The Fig. 9 presents the system's response when a defective bolt is detected. The system marks the bolt with a red bounding box and labels it as defective, along with the confidence score. The captured and processed images are displayed together for comparison and validation. Arduino communication remains active, enabling the sorting mechanism to act on the defect classification. The defective bolt counter increments accordingly, demonstrating the system's ability to accurately identify faulty components in real time.

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VII. DISCUSSIONS

The combined results from training and evaluating YOLOv8, YOLOv9, YOLOv11, and YOLOv12 clearly show that modern object detection models are highly effective for real-time bolt defect detection in a Cyber-Physical System (CPS). All four models demonstrated strong learning behaviour, with consistent reductions in box loss, classification loss, and DFL loss, proving their ability to accurately localise defects and distinguish between defect types. Key performance metrics-precision, recall, mAP50, and mAP50–95—show steady improvement across training, highlighting reliable detection of both simple and complex bolt defects under varying lighting conditions and backgrounds. Among the models, YOLOv8 and YOLOv12 showed especially stable convergence and high accuracy, making them strong candidates for industrial deployment where low false detections and consistent output are essential. When comparing all models, YOLOv8 stands out as the most balanced option in terms of speed, accuracy, and generalisation, making it particularly well-suited for real-time CPS applications. While YOLOv12 achieved competitive precision and slightly better mAP values, YOLOv8 delivered superior stability during both training and validation, with smoother improvement across all core metrics. The hardware setup effectively supported these models, allowing seamless coordination between image capture, inference, and mechanical actuation. Real-time system outputs confirm that the CPS not only detects defects accurately but also responds instantly by triggering the servo-based sorting mechanism. Overall, the results show that the proposed system is robust, scalable, and highly capable of enabling automated quality inspection in modern industrial environments.

VIII. CONCLUSION

In conclusion, the project "Development of a Cyber-Physical System in Real-Time Bolt Defect Detection using Machine Learning Based Automated Quality Control" successfully shows how a fast, accurate, and intelligent industrial inspection system can be built by combining YOLOv8 with embedded edge computing. The trained model demonstrates strong capability in detecting cracks, rust, deformation, and missing bolts, achieving 91.8% accuracy on the custom dataset and performing far better than traditional manual inspection in both precision and consistency. Experimental tests confirm that the system can sort bolts reliably during live conveyor operation, while temporal frame analysis helps maintain stable inference speeds and reduces false positives, even under varying lighting, motion, and background conditions.

The CPS architecture integrates real-time detection, automated actuation, and a live monitoring dashboard, resulting in higher inspection throughput, better operational efficiency, and complete defect traceability. The validated performance metrics clearly show that the system successfully bridges physical manufacturing processes with intelligent analytics, supporting zero-defect production, predictive maintenance, and fully automated quality assurance aligned with Industry 4.0 goals. Looking forward, the system provides a strong foundation for future enhancements, wider scalability, and deployment across diverse industrial environments.

IX. FUTURE SCOPE

- **3D and Depth-Aware Inspection**
  Future improvements can include adding 3D or depth-sensing technologies such as stereo vision or structured-light systems. These sensors would help detect subtle geometric defects like slight bends, thread deformation, or fine cracks that may not be visible in standard 2D images. This upgrade is especially valuable for safety-critical fasteners where hidden flaws must be identified.
- **Adaptive and Continual Learning**
  The system can be upgraded to learn automatically from new defect cases over time. By incorporating a feedback loop where operators correct incorrect predictions, the model can refine itself without requiring a full retraining cycle. This makes the system more resilient and accurate as factory conditions and defect types evolve.
- **Multi-View and 360° Surface Coverage**
  Using multiple coordinated cameras or a rotating inspection mechanism will allow full 360° coverage of each bolt. Combining different angles removes blind spots and significantly improves the detection of defects that may be hidden from a single viewpoint.
- **Integration with Industrial Systems**
  Connecting the inspection system to existing manufacturing platforms like MES or ERP can provide real-time defect traceability, production analytics, and improved decision-making. This integration enhances process control, helps monitor quality trends, and strengthens supplier evaluation.

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Together, these advancements build on a validated system that already links real-time industrial processes with intelligent automation. The current framework forms a strong foundation for broader deployment of AI-driven quality inspection in modern manufacturing environments.

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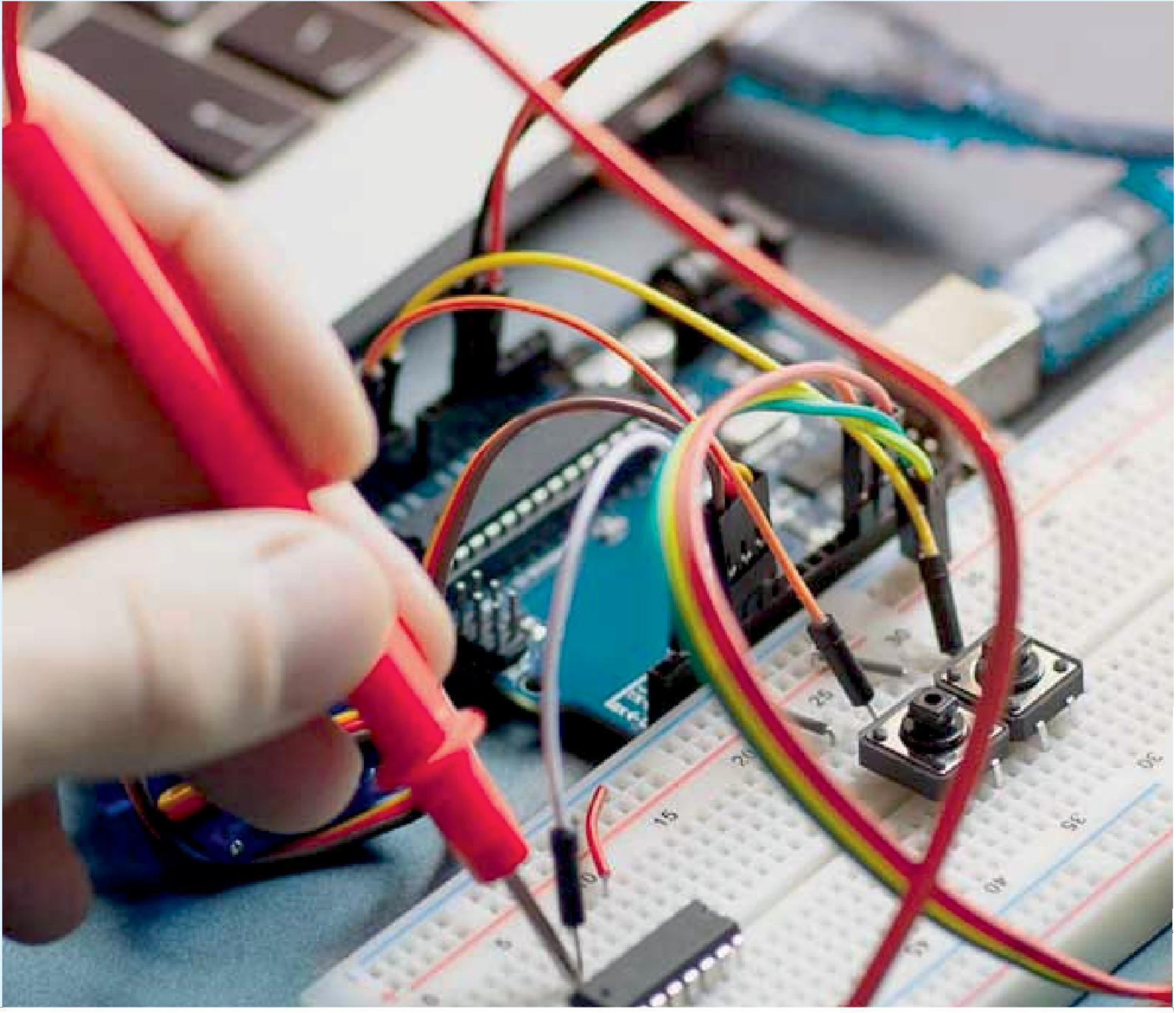

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